## Machine-learning Based Heuristics for Propositional SAT Solving

### Ezequiel Orbe

Grupo de Procesamiento de Lenguaje Natural Fa.M.A.F., Universidad Nacional de Córdoba

06/12/10

## Introducing Myself...

### Info

- Me: Alejandro Ezequiel Orbe
- Supervisors: Gabriel Infante Lopez & Carlos Areces
- Research Area: Propositional Logic ∩ Machine Learning.

### Research Topic

Machine-learning based Heuristics for Propositional SAT.

### Outline of the Talk

Machine-learning based heuristics for Propositional SAT

2 Exploiting Symmetry in Propositional SAT Solving

## Background

### Facts about SAT Solving

- Propositional satisfiability (SAT)  $\Rightarrow$  well-known  $\mathcal{NP}$ -complete problem.
- Relevance  $\Rightarrow$  Many  $\mathcal{NP}$ -problems mapped into a SAT problem.
- Two types of solvers ⇒ Complete & Incomplete.
- Complete Solvers ⇒ Conflict-driven (CDCL) & Look-ahead.
- General purpose heuristics.

## Background

#### Previous Work

- Understanding Random SAT: Beyond the Clauses-to-Variables Ratio. Nudelman et al. 2007.
- Hierarchical hardness models for SAT. Lin Xu et al. 2007.
- Restart Strategy Selection using Machine Learning Techniques. Toby Walsh et al. 2009.
- Problem-Sensitive Restart Heuristics for the DPLL
   Procedure. Carsten Sinz et al. 2009.

### Our Research...

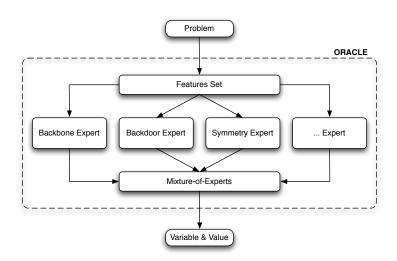
#### Goals

- Automatically find structure in problems from an specific domain.
- Exploit the structure to guide the search.

### Setup

- Problem Generator ⇒ Training Material.
- Features Set ⇒ Captures structural properties.
- Oracle ⇒ Branching Heuristic ⇒ Decision & Direction
- Oracle ⇒ Probability Distribution ⇒ Mixture-of-experts.

## Setup



#### Informal Definition

- In general ⇒ The symmetry of a discrete object is a permutation of its components that leaves the object intact.
- In SAT-solving ⇒ mapping of a problem into itself that preserves its structure and solutions.

### Example

- $\mathcal{T} = (\neg A \lor B \lor C) \land (A \lor \neg B \lor C).$
- $\bullet \ \theta_1 = \{A \mapsto B, B \mapsto A\}$

$$\theta_1(\mathcal{T}) = (\neg B \lor A \lor C) \land (B \lor \neg A \lor C)$$

 $\bullet \ \theta_2 = \{A \mapsto \neg A, B \mapsto \neg B\}$ 

$$\theta_2(\mathcal{T}) = (\neg \neg A \lor \neg B \lor C) \land (\neg A \lor \neg \neg B \lor C)$$

## Example

#### How can we use it?

- Symmetries creates a partition in the assignment set.
- In search problems, if there are several points of the search space that are symmetric ⇒ just explore one of them.

### Example

$$\bullet \quad \mathcal{T} = (\neg A \lor B \lor C) \land (A \lor \neg B \lor C).$$

$$\bullet \ \theta_1 = \{A \mapsto B, B \mapsto A\}$$

Α	В	C	$\mid \mathcal{T} \mid$
0	0	0	1
0	0	1	1
0	1	0	0
0	1	1	1
1	0	0	0
1	0	1	1
1	1	0	1
1	1	1	1

$$\begin{array}{l} \theta_1(000) = 000 \\ \theta_1(001) = 001 \\ \theta_1(010) = 100 \\ \theta_1(011) = 101 \\ \theta_1(100) = 010 \\ \theta_1(101) = 011 \\ \theta_1(110) = 110 \\ \theta_1(111) = 111 \end{array}$$

$$C_0 = \{000\}$$

$$C_1 = \{001\}$$

$$C_2 = \{010, 100\}$$

$$C_3 = \{011, 101\}$$

$$C_4 = \{110\}$$

$$C_5 = \{111\}$$

#### Notation & Definitions

- Let  $V = \{x_1, x_2, \dots, x_n\}$  be a set of boolean variables.
- Lets assume a total order of the variables in V:  $x_1 < x_2 < \ldots < x_n$
- Let  $L = \{x_1, \neg x_1, x_2, \neg x_2, \dots, x_n, \neg x_n\}$  be the set of literals of variables in V.
- ullet Let Sym(L) be the symmetric group of the set L of literals.
- If  $v \in L$  and  $\theta \in Sym(L)$ , the image of v under  $\theta$  is denoted by  $v^{\theta}$ .

#### Definition

- Let T be a theory over L and let  $\theta \in Sym(L)$ .
- The permutation  $\theta$  is a **symmetry**, or **automorphism**, of T iff  $T^{\theta} = T$ .
- The set of symmetries of T is a subgroup of Sym(L) and is denoted by Aut(T).

#### Definition

- A truth assignment for a set of variables V is a function  $A: V \to \{0, 1\}$ .
- A truth assignment A of V is called a **model** of theory T if A(T)=1.
- The set of models of T is denoted  $\mathcal{M}(T)$ .

#### Some facts...

- Symmetries can be viewed as acting on assignments.
- If  $\theta \in Sym(L)$  then  $\theta$  acts on the set of truth assignments by mapping  $A \mapsto {}^{\theta}A$  where  ${}^{\theta}A(v) = A(v^{\theta})$  for  $v \in L$ .
- Hence, if T is a theory over L,  $A(T^{\theta}) = {}^{\theta}A(T)$ .
- ullet Any symmetry of T maps models of T to models of T, and non-models of T to non-models

### **Proposition**

Let T be a theory over V,  $\theta \in Aut(T)$ , and A a truth assignment of V. Then  $A \in \mathcal{M}(T)$  iff  $\theta A \in \mathcal{M}(T)$ 

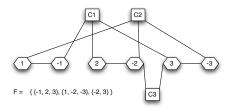
#### More facts...

- Aut(T) induces an equivalences relation on the set of truth assignments of L, wherein  $A \sim B$  if  $B = {}^{\theta} A$  for some  $\theta \in Aut(T)$
- The equivalence classes are the *orbits* of Aut(T) in the set of assignments.
- Any equivalence class contains only models of T or contains no models of T.
- This indicates why symmetries can be used to reduce search: we can determine whether T has a model by visiting each equivalence class rather than visiting each truth assignment.

## Symmetry Detection

#### How can we do it?

- The problem of extracting symmetries of a CNF formula is reduced to the colored graph automorphism problem.
- Main idea: Find a colored graph whose symmetry group is isomorphic to the symmetry group of the CNF formula.
- Available Tool ⇒ Saucy
- Generates a graph with 2V + C vertices.



### Pre-processing Approach

- Complete Symmetry Breaking:
  - Augment the original formula with Symmetry Breaking Predicates (SBP).
  - Pros:
    - Each predicate select exactly on representative assignment from each equivalence class.
  - Cons:
    - The size of the predicate can exceed significantly the size of the original formula.

$$egin{aligned} \operatorname{PP}\left(\pi;X
ight) &= \operatorname{leq}\left(X,X^{\pi}
ight) \ &= igwedge_{i \in [0,n-1]} \left[ igwedge_{j \in [i+1,n-1]} \left(x_{j} = x_{j}^{\pi}
ight) 
ight] 
ightarrow \left(x_{i} \leqslant x_{i}^{\pi}
ight) \end{aligned}$$

### Pre-processing Approach

- Partial Symmetry Breaking
  - Full symmetry breaking is unfeasible.
  - Pros:
    - Only breaks symmetries for the set of irredundant generators of the symmetry group.
  - Cons:
    - A partial SBP selects the least assignment in each orbit of the symmetry group but may include other assignments as well.

### In-processing Approach

- Dynamic Symmetry Breaking
  - Breaks symmetries during the search.
  - There is little mention to this approach in the literature.
  - Pros:
    - Identify local symmetries.
    - Avoid the creation of SBPs.
    - Boost the performance of conflict-driven learning.
  - Cons:
    - Difficult to integrate with current solvers.

### Our approach to Symmetry-Breaking

- Dynamic Partial Symmetry Breaking.
- Use the set of irredundant generators.
- Integration of symmetry detection in the search process.
- Symmetry breaking as component of a complex heuristic (Symmetry Expert).

### Results



# Thank you!