

# Cost Minimizing Search on Non-prenex and Non-CNF QBF<sup>1</sup>

Soonho Kong

Programming Research Laboratory  
Seoul National University

March 21, 2008

---

<sup>1</sup>Work done with Dr. Ting Zhang in Microsoft Research Asia

1 QBF Problem

2 Motivation

3 Cost Minimizing Search

4 Performance

5 Future Work

6 References

# QBF

## Quantified Boolean Formulae

- Quantifiers:  $\forall, \exists$
- All variables are Boolean variables.
- Logical Operator:  $\wedge, \vee, \neg$

# Example

$$\psi_1 = \forall x \exists y (x \vee \neg y)$$

True

# Example

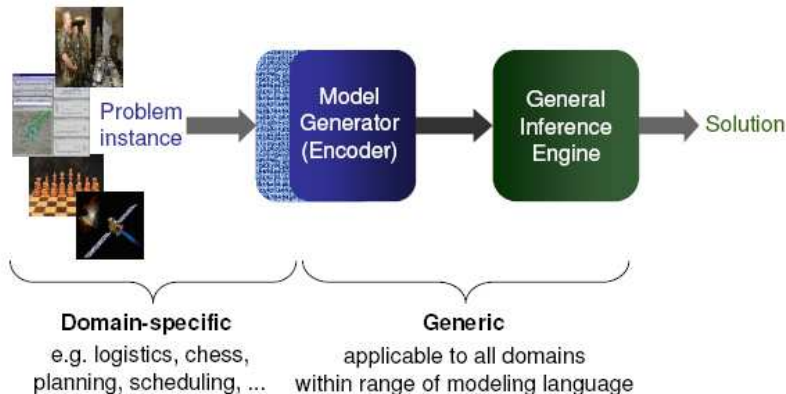
$$\psi_2 = \forall x \exists y (x \wedge \neg y)$$

False

# QBF Problem

- The QBF problem is to determine its truth value.
- In complexity theory, it is PSPACE problem.
- At least as hard as NP.

# Why is QBF solving important?



[Credit: A. Sabharwal, B. Selman, Beyond Traditional SAT Reasoning, AAAI 2007 Tutorial]

# Why is QBF solving important?

QBF compactly encode many problems in CSE.

- Automated Plannig
- Scheduling
- Bounded Model Checking(BMC)
- Electronic Design Automation

Improvement in solving engine affects many application areas.



# Compact Encoding

- QBF provides a compacter encoding than SAT.
- Transforming QBF into equivalent SAT increases space exponentially.
  - QBF :  $\forall x \exists y \exists z (x \vee \neg y \vee z)$
  - SAT :  $(\exists y \exists z (\top \vee \neg y \vee z)) \wedge (\exists y \exists z (\perp \vee \neg y \vee z))$

# Existing Approach

- Search-based
- Q-Resolution
- Symbolic Skolemization

# Existing Approach

Search-based QBF solving is dominant.

- Search-based technique is dominant in SAT solving.
- People tried to apply and extend those techniques to QBF solving problem.

# Search-based QBF solving

Search-based QBF solvers require normalized input.

- Prenex Form
- Conjunctive Normal Form(CNF)

# Normalized Input - Prenex Form

## Prenex Form

- (X) :  $\forall x(\exists y(x \vee y) \wedge (\exists z(x \vee z)))$
- (O) :  $\forall x\exists y\exists z((x \vee y) \wedge (x \vee z))$

# Normalized Input - CNF

## Conjunctive Normal Form(CNF)

- Literal : Variable or Negation of Variable

$x, \neg x$

- Clause : Disjunction of Literals

$(x \vee \neg y \vee z)$

- CNF : Conjunction of Clauses

$(x \vee \neg y \vee z) \wedge (\neg x \vee y \vee \neg z)$

# Why should be “prenex and CNF”?

## Binary Constraint Propagation(BCP)

# Why “prenex and CNF”?

## Binary Constraint Propagation(BCP)

BCP propagate one assignment  
and deduce another another assignment  
without searching the space.



# Why “prenex and CNF”?

BCP is a “Founding block” for

- non-chronological backtracking
- conflict-driven learning

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\forall x \exists y \exists z ((x \vee \neg y \vee z) \wedge (\neg x \vee \neg y \vee \neg z))$$

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\forall x \exists y \exists z ((x \vee \neg y \vee z) \wedge (\neg x \vee \neg y \vee \neg z))$$

Try  $x = \top$ .

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\exists y \exists z ((\top \vee \neg y \vee z) \wedge (\perp \vee \neg y \vee \neg z))$$

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\exists y \exists z (\neg y \vee \neg z)$$

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\exists y \exists z (\neg y \vee \neg z)$$

Try  $y = \top$

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\exists z(\perp \vee \neg z)$$

# Binary Constraint Propagation(BCP) Example

## Binary Constraint Propagation(BCP)

$$\exists z(\neg z)$$

Now,  $z$  must be  $\perp$  and it makes the formula satisfied.



# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\forall x \exists y \exists z ((x \vee \neg y \vee z) \wedge (\neg x \vee \neg y \vee \neg z))$$

Go back to try  $x = \perp$  because of  $\forall x$ .

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\forall x \exists y \exists z ((\perp \vee \neg y \vee z) \wedge (\top \vee \neg y \vee \neg z))$$

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\exists y \exists z (\neg y \vee z)$$

Try  $y = \top$ .

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\exists z(\perp \vee z)$$

# Binary Constraint Propagation(BCP) Example

## Binary Constraint Propagation(BCP)

$$\exists z(\vee z)$$

Now we know that  $z$  should be  $\top$   
and it makes the formula satisfied.

# Binary Constraint Propagation(BCP) Example

Binary Constraint Propagation(BCP)

$$\forall x \exists y \exists z ((\perp \vee \neg y \vee z) \wedge (\top \vee \neg y \vee \neg z))$$

Now we know that the formula is true.

# Problem

It is necessary to have prenex and CNF to conduct BCP.

# Problem

However,  
QBF encodings from the real world applications  
never come in prenex and CNF.



# Problem

Prenex converting and CNF converting are not free.

# Problem - CNF

Converting into equivalent CNF takes exponential time.

# Problem - CNF

Tseytin introduced linear-time CNF converting method.  
However,  
it introduces new existentially quantified variables.

# Problem - CNF

Our experiment shows  
total number of variables increase by  
*four times*.

# Problem - prenex form

Converting into prenex form enlarges the search space by

- widening quantifier scope
- introducing dependency to the variables which were independent

# Problem - prenex form

$$\forall x \psi_1(x) \wedge \exists y \psi_2(y) \wedge \forall z \psi_3(z) \wedge \exists w \psi_4(w)$$

is converted into

$$\forall x \exists y \forall z \exists w (\psi_1(x) \wedge \psi_2(y) \wedge \psi_3(z) \wedge \psi_4(w))$$

# Motivation

Is there another way to solve QBF  
without converting input into prenex and CNF?

# Motivation

Is there another direction in QBF solving  
which is not based on boolean constraint propagation?



# Motivation

Yes, there is!  
Naive algorithm solves QBF without BCP.

# Motivation - Naive Algorithm

$$\llbracket \top \rrbracket := \top \quad \llbracket \neg \top \rrbracket := \perp \quad \llbracket \bigwedge_i \varphi_i \rrbracket := \bigwedge_i \llbracket \varphi_i \rrbracket$$

$$\llbracket \perp \rrbracket := \perp \quad \llbracket \neg \perp \rrbracket := \top \quad \llbracket \bigvee_i \varphi_i \rrbracket := \bigvee_i \llbracket \varphi_i \rrbracket$$

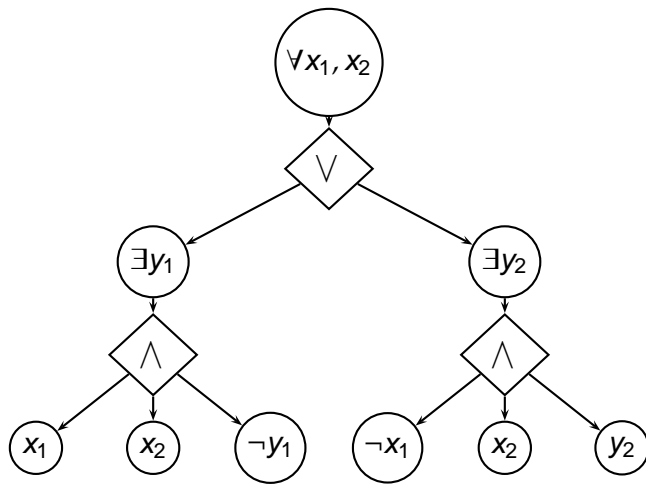
$$\llbracket \forall \mathbf{x} \varphi \rrbracket := \llbracket \varphi[\mathbf{x} \mapsto \top] \rrbracket \wedge \llbracket \varphi[\mathbf{x} \mapsto \perp] \rrbracket$$

$$\llbracket \forall \bar{\mathbf{x}} \varphi \rrbracket := \llbracket \forall (\bar{\mathbf{x}} \setminus \mathbf{x}_1) (\varphi[\mathbf{x}_1 \mapsto \top]) \rrbracket \wedge \llbracket \forall (\bar{\mathbf{x}} \setminus \mathbf{x}_1) (\varphi[\mathbf{x}_1 \mapsto \perp]) \rrbracket$$

$$\llbracket \exists \mathbf{x} \varphi \rrbracket := \llbracket \varphi[\mathbf{x} \mapsto \top] \rrbracket \vee \llbracket \varphi[\mathbf{x} \mapsto \perp] \rrbracket$$

$$\llbracket \exists \bar{\mathbf{x}} \varphi \rrbracket := \llbracket \exists (\bar{\mathbf{x}} \setminus \mathbf{x}_1) (\varphi[\mathbf{x}_1 \mapsto \top]) \rrbracket \vee \llbracket \exists (\bar{\mathbf{x}} \setminus \mathbf{x}_1) (\varphi[\mathbf{x}_1 \mapsto \perp]) \rrbracket$$

# Example



# Motivation - Naive Algorithm

But its performance is poor.  
2 - 4 orders of magnitude slower  
than the state-of-the-art solvers.

# Motivation

Is there an “efficient” search-based method to solve QBF without conducting boolean constraint propagation?

# Cost Minimizing Search

## Cost Minimizing Search

Based on the same naive algorithm shown before.

# Preprocessing

Push Quantifiers as Further as Possible  
to Reduce Search Space

$$\forall x(\varphi \wedge \psi) \equiv (\forall x\varphi) \wedge \psi, \quad \forall x(\varphi \vee \psi) \equiv (\forall x\varphi) \vee \psi,$$

$$\exists x(\varphi \wedge \psi) \equiv (\exists x\varphi) \wedge \psi, \quad \exists x(\varphi \vee \psi) \equiv (\exists x\varphi) \vee \psi.$$

$\varphi, \psi \in \text{QBF}$  and  $x$  a variable not occurring *free* in  $\psi$ . For example

$$\forall x \exists y \exists z ((x \vee y) \wedge (x \vee z)) \rightarrow \forall x (\exists y (x \vee y) \wedge (\exists z (x \vee z)))$$

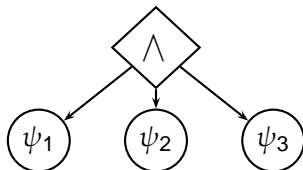
# Observation

We can reduce the time  
by exploiting “short-circuit” property of  $\wedge$  and  $\vee$  operator.



# Observation

Once we found a desired result from the subnode,  
We do not have to continue the evaluation.



If  $\psi_1$  is false, then whole formula turns out to be false.

# Observation

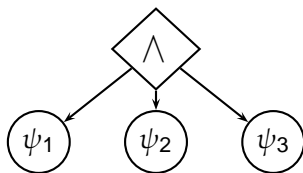
Since operators  $\wedge$  and  $\vee$  are *commutative*,  
we can *sort* the operands and exploit short-circuit property.

# Considerations

Consider two things:

1. Truth Probability
2. Expected Search Space

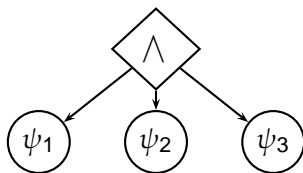
# Truth Probability



$$P(\psi_1) = 0.8, P(\psi_2) = 0.6, P(\psi_3) = 0.3$$

It is better to sort  $\psi_i$  to  $\psi_3, \psi_2, \psi_1$  and try  $\psi_3$  first.

# Expected Search Space



$$S(\psi_1) = 300, S(\psi_2) = 60, S(\psi_3) = 90$$

It is better to sort  $\psi_i$  to  $\psi_2, \psi_3, \psi_1$  and try  $\psi_2$  first.

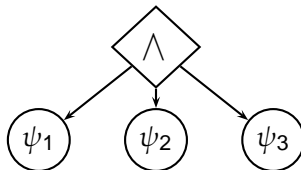
# Cost

In general, truth probability and expected search space vary at the same time. We need a *single measure* to sort the subnode  $\psi_i$ s. We introduce the concept of *cost*.

Cost = Probability of Being Useless  $\times$  Expected Search Space

# Cost Minimizing Search

Conduct depth-first cost minimizing search



$$P(\psi_1) = 0.8 \quad P(\psi_2) = 0.6 \quad P(\psi_3) = 0.3$$

$$S(\psi_1) = 300 \quad S(\psi_2) = 60 \quad S(\psi_3) = 90$$

$$C(\psi_1) = 24 \quad C(\psi_2) = 36 \quad C(\psi_3) = 27$$

It is better to sort  $\psi_i$  to  $\psi_1, \psi_3, \psi_2$  and try  $\psi_1$  first.

# Probability Calculation

$$1 \quad \varphi \equiv x \mid \neg x$$

$$P(x) = P(\neg x) = \frac{1}{2}$$

$$2 \quad \varphi \equiv \bigwedge_{i=1}^n \varphi_i$$

$$P\left(\bigwedge_{i=1}^n \varphi_i\right) = \prod_{i=1}^n P(\varphi_i)$$

$$3 \quad \varphi \equiv \bigvee_{i=1}^n \varphi_i$$

$$P\left(\bigvee_{i=1}^n \varphi_i\right) = 1 - \prod_{i=1}^n (1 - P(\varphi_i))$$



# Probability Calculation

4  $\varphi \equiv \forall \bar{x} \psi$

$$P(\forall \bar{x} \psi) = \prod_{i=1}^{2^{|\bar{x}|}} P(\psi) = (P(\psi))^{(2^{|\bar{x}|})}$$

5  $\varphi \equiv \exists \bar{x} \psi$

$$P(\neg \forall \bar{x} \neg \psi) = 1 - P(\forall \bar{x} \neg \psi) = 1 - (1 - P(\psi))^{(2^{|\bar{x}|})}$$

# Expected Search Space Calculation

$$1 \quad \varphi \equiv x \mid \neg x$$

$$S(x) = S(\neg x) = 1$$

# Expected Search Space Calculation

$$2 \quad \varphi \equiv \bigwedge_{i=1}^n \varphi_i$$

$$S\left(\bigwedge_{i=1}^n \varphi_i\right) = \sum_{i=1}^n \widehat{P}_i(\varphi) \widehat{S}_i(\varphi) + \left(\prod_{j=1}^n P(\varphi_j)\right) \left(\sum_{j=1}^n S(\varphi_j)\right)$$

$$\widehat{P}_i(\varphi) = \left(\prod_{j=1}^{i-1} P(\varphi_j)\right) (1 - P(\varphi_i)),$$

$$\widehat{S}_i(\varphi) = \sum_{j=1}^i S(\varphi_j)$$

where  $\widehat{P}_i(\varphi)$  is the probability that  $\llbracket \varphi_j \rrbracket = \top$  for any  $1 \leq j \leq i-1$  and  $\llbracket \varphi_i \rrbracket = \perp$ .

# Expected Search Space Calculation

- 2**  $\varphi \equiv \bigwedge_{i=1}^n \varphi_i$  Introducing an imaginary element  $\varphi_{n+1}$  such that  $P(\varphi_{n+1}) = 0$  and  $S(\varphi_{n+1}) = 0$ , we simplify to

$$S\left(\bigwedge_{i=1}^n \varphi_i\right) = \sum_{i=1}^{n+1} \widehat{P}_i(\varphi) \widehat{S}_i(\varphi)$$

# Expected Search Space Calculation

$$\mathbf{3} \quad \varphi \equiv \bigvee_{i=1}^n \varphi_i$$

$$S\left(\bigvee_{i=1}^n \varphi_i\right) = \sum_{i=1}^{n+1} \tilde{P}_i(\varphi) \widehat{S}_i(\varphi)$$

$$\tilde{P}_i(\varphi) = \left( \prod_{j=1}^{i-1} (1 - P(\varphi_j)) \right) P(\varphi_i)$$

where  $P(\varphi_{n+1})$  is an imaginary element set to 1.

$$\mathbf{4} \quad \varphi \equiv \forall \bar{x} \psi \text{ In the general case where } \bar{x} \text{ has } |\bar{x}| \text{ elements, we have}$$

$$S(\forall \bar{x} \psi) = (1 + P(\psi))^{|\bar{x}|} S(\psi)$$

$$\mathbf{5} \quad \varphi \equiv \exists \bar{x} \psi$$

$$S(\exists \bar{x} \psi) = (2 - P(\psi))^{|\bar{x}|} S(\psi)$$

# Cost Calculation

1  $\varphi \equiv x \mid \neg x$

Leaf nodes have no child and hence no cost assigning is needed.

2  $\varphi \equiv \bigwedge_{i=1}^n \varphi_i$

$$C(\varphi_i) = P(\varphi_i)S(\varphi_i)$$

3  $\varphi \equiv \bigvee_{i=1}^n \varphi_i$

$$C(\varphi_i) = (1 - P(\varphi_i))S(\varphi_i)$$

4  $\varphi \equiv \forall \bar{x} \psi$

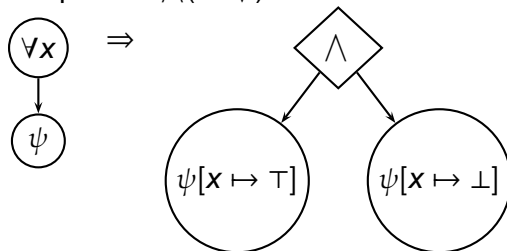
$$C(\psi_i) = P(\psi_i)S(\psi_i)$$

5  $\varphi \equiv \exists \bar{x} \psi$

$$C(\psi_i) = (1 - P(\psi_i))S(\psi_i)$$

# Quantifier Node

During the evaluation quantifier will be replaced with logical operator  $\wedge$  (or  $\vee$ ) and instantiated child node.



# Quantifier Node

Therefore, we can apply CMS for the quantifier.

Instead of sorting the subnodes,  
we control the variable instantiation order.



# Variable Instantiation Order

If a quantifier node has  $n$  variables,  
then there could be  $2^n$  variable instantiations.

$$\forall \{x_1, x_2, \dots, x_n\} \psi$$

$$C(\psi[x_1 \mapsto \top, x_2 \mapsto \top, \dots, x_n \mapsto \top]) = ?$$

$$C(\psi[x_1 \mapsto \top, x_2 \mapsto \top, \dots, x_n \mapsto \perp]) = ?$$

$$C(\psi[x_1 \mapsto \top, x_2 \mapsto \perp, \dots, x_n \mapsto \top]) = ?$$

$$C(\psi[x_1 \mapsto \top, x_2 \mapsto \perp, \dots, x_n \mapsto \perp]) = ?$$

...

# Variable Instantiation Order

Naive approach would take  $2^n$  cost calculations  
to find minimal cost variable instantiation.

That is prohibitively expensive.

# Variable Instantiation Order

We approximate the cost of an instantiation

$$C(\psi[x_1 \mapsto b_1][x_2 \mapsto b_2] \cdots [x_n \mapsto b_n]) = \frac{\sum_{i=1}^n C(\psi[x_i \mapsto b_i])}{n}$$

Using this approximation  
we only need to compute  $2n$  single-variable instantiations.

# Variable Instantiation Order

However, it is not efficient enough  
as we still have  $2^{|\bar{x}|}$  combinations to compute and sort.

$$C(\psi[x_1 \mapsto \top, x_2 \mapsto \top, \dots, x_n \mapsto \top]) = ?$$

$$C(\psi[x_1 \mapsto \top, x_2 \mapsto \top, \dots, x_n \mapsto \perp]) = ?$$

$$C(\psi[x_1 \mapsto \top, x_2 \mapsto \perp, \dots, x_n \mapsto \top]) = ?$$

$$C(\psi[x_1 \mapsto \top, x_2 \mapsto \perp, \dots, x_n \mapsto \perp]) = ?$$

Here we need another heuristic.

# Variable Instantiation Order - Preference Function

First we fix an instantiation order for every single variable by the notion of *preference function*

$$\text{Pref}(x_i) = \begin{cases} \top & \text{if } C(\psi[x_i \mapsto \top]) \leq C(\psi[x_i \mapsto \perp]) \\ \perp & \text{otherwise} \end{cases}$$

For a variable  $x$ ,  $\text{Pref}(x)$  returns the Boolean assignment which has the lower cost.

For example,  
If  $C(\psi[x_i \mapsto \top]) = 10$  and  $C(\psi[x_i \mapsto \perp]) = 3$ ,  
then  $\text{Pref}(x_i) = \perp$ .

# Variable Instantiation Order - New Algorithm

We use Pref to modify the evaluation function  $\llbracket \cdot \rrbracket$  as follows.

$$\llbracket \forall x \varphi \rrbracket := \llbracket \varphi[x \mapsto \text{Pref}(x)] \rrbracket \wedge \llbracket \varphi[x \mapsto \neg \text{Pref}(x)] \rrbracket$$

$$\begin{aligned} \llbracket \forall \bar{x} \varphi \rrbracket &:= \llbracket \forall (\bar{x} \setminus x_1) (\varphi[x_1 \mapsto \text{Pref}(x_1)]) \rrbracket \\ &\quad \wedge \llbracket \forall (\bar{x} \setminus x_1) (\varphi[x_1 \mapsto \neg \text{Pref}(x_1)]) \rrbracket \end{aligned}$$

$$\llbracket \exists x \varphi \rrbracket := \llbracket \varphi[x \mapsto \text{Pref}(x)] \rrbracket \vee \llbracket \varphi[x \mapsto \neg \text{Pref}(x)] \rrbracket$$

$$\begin{aligned} \llbracket \exists \bar{x} \varphi \rrbracket &:= \llbracket \exists (\bar{x} \setminus x_1) (\varphi[x_1 \mapsto \text{Pref}(x_1)]) \rrbracket \\ &\quad \vee \llbracket \exists (\bar{x} \setminus x_1) (\varphi[x_1 \mapsto \neg \text{Pref}(x_1)]) \rrbracket. \end{aligned}$$

# Variable Instantiation Order

In this algorithm, variable order induces instantiation order.

Example

$$\varphi = \forall x_1, x_2, x_3 \psi$$

where  $\text{Pref}(x_1) = \top$ ,  $\text{Pref}(x_2) = \perp$ , and  $\text{Pref}(x_3) = \perp$ .

Instantiation Order		
$\{ [x_1 \mapsto \top],$	$[x_2 \mapsto \perp],$	$[x_3 \mapsto \perp] \}$
$\{ [x_1 \mapsto \top],$	$[x_2 \mapsto \perp],$	$[x_3 \mapsto \top] \}$
$\{ [x_1 \mapsto \top],$	$[x_2 \mapsto \top],$	$[x_3 \mapsto \perp] \}$
...		
$\{ [x_1 \mapsto \perp],$	$[x_2 \mapsto \top],$	$[x_3 \mapsto \top] \}$

# Variable Instantiation Order

We introduce the significance of variable  $x_i$  as

$$\text{Diff}(x_i) = C(\psi[x_i \mapsto \neg \text{Pref}(x_i)]) - C(\psi[x_i \mapsto \text{Pref}(x_i)]).$$

For example,

If  $C(\psi[x_i \mapsto \top]) = 10$  and  $C(\psi[x_i \mapsto \perp]) = 3$ ,  
then  $\text{Pref}(x_i) = \perp$  and  $\text{Diff}(x_i) = 7$ .

By Sorting  $\bar{x}$  by Diff in descending order, we can have better instantiation order.



# Variable Instantiation Order - Example

	$x_1$	$x_2$	$x_3$
$C(\psi[x_i \mapsto \top])$	3	4	5
$C(\psi[x_i \mapsto \perp])$	2	7	3

# Variable Instantiation Order - Example

	$x_1$	$x_2$	$x_3$
$C(\psi[x_i \mapsto \top])$	3	<u>4</u>	5
$C(\psi[x_i \mapsto \perp])$	<u>2</u>	7	<u>3</u>
$\text{Diff}(x_i)$	1	3	2

Pref is marked and Diff is calculated.

# Variable Instantiation Order - Example

	$x_2$	$x_3$	$x_1$
$C(\psi[x_i \mapsto \top])$	<u>4</u>	5	3
$C(\psi[x_i \mapsto \perp])$	7	<u>3</u>	<u>2</u>
$\text{Diff}(x_i)$	3	2	1

$\bar{x}$  is sorted by Diff.

Instantiation Order	Cost
$\{ [x_2 \mapsto \top], [x_3 \mapsto \perp], [x_1 \mapsto \perp] \}$	3
$\{ [x_2 \mapsto \top], [x_3 \mapsto \perp], [x_1 \mapsto \top] \}$	3.3
$\{ [x_2 \mapsto \top], [x_3 \mapsto \top], [x_1 \mapsto \perp] \}$	3.6
...	...
$\{ [x_2 \mapsto \perp], [x_3 \mapsto \top], [x_1 \mapsto \top] \}$	5

# Experiment - Configuration

Almost the same configuration with QBFEVAL'08

- CPU : Intel Pentium D 3.0 GHz
- RAM : 4GB
- OS : Ubuntu/GNU Linux 7.10
- Timeout : 600 sec

# Experiment - Test Suite

- QBF 1.0 benchmark from QBFLIB
- 92 instances of non-prenex and non-CNF QBF
- generated from the computation of state space diameters of four models:
  - chain of inverters (Ring, 20 instances)
  - semaphore-based mutual exclusion protocol (Semaphore, 16 instances)
  - chain of inverters (Counter, 45 instances)
  - distributed mutual exclusion protocol (DME, 11 instances)

# State-of-the-art Solvers

Three state-of-the-art solvers are chosen:

- QuBE6.0
- sKizzo v0.8.2-beta
- Quantor 3.0 with Picosat-632.

They only accept prenex and CNF instances. We used the converter provided by QBFLIB and did not include conversion time in running time.

# Comparison Result

<b>Model</b>	<b>Quantor</b>	<b>sKizzo</b>	<b>QuBE</b>	<b>CMS</b>
Ring	10/20	11/20	14/20	20/20
Semaphore	16/16	14/16	13/16	16/16
Counter	28/45	33/45	29/45	27/45
DME	0/11	0/11	6/11	0/11
<b>Total</b>	<b>54/92</b>	<b>58/92</b>	<b>62/92</b>	<b>63/92</b>

Table: Number of solved instances

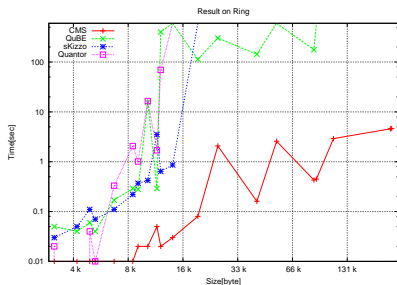
# Comparison Result

<b>Model</b>	<b>Quantor</b>	<b>sKizzo</b>	<b>QuBE</b>	<b>CMS</b>
Ring	77,402	91,780	250,351	973,093
Semaphore	336,596	248,583	219,908	336,596
Counter	341,074	707,679	409,578	308,826
DME	0	0	633,770	0
<b>Total</b>	<b>755,072</b>	<b>1,048,042</b>	<b>1,513,607</b>	<b>1,618,515</b>

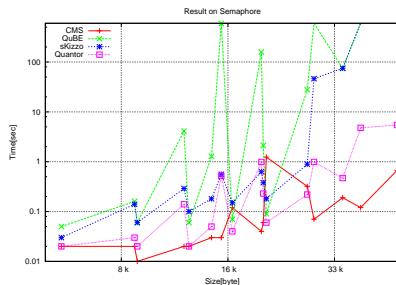
Table: Total size of solved instances (in bytes)



# Comparison Result



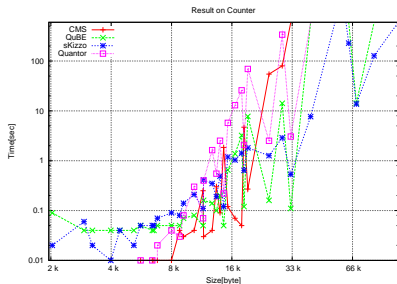
(a) Ring



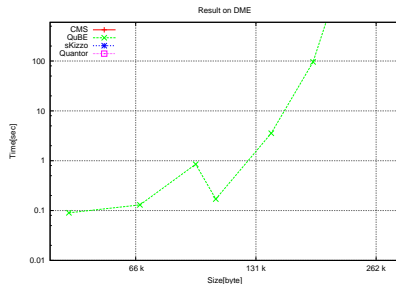
(b) Semaphore

Figure: Performance comparison between *CMS* and three state-of-the-art solvers on QBF 1.0 test suite

# Comparison Result



(c) Counter



(d) DME

Figure: Performance comparison between *CMS* and three state-of-the-art solvers on QBF 1.0 test suite

# Future Work

- Using better search algorithm such as  $A^*$  instead of depth-first search.
- Using BDD instead of tree representation.
- Extending to support more logical operator such as XOR and EQUIV which frequently occur in electronic design.

# References



Giunchiglia, E., Narizzano, M., Tacchella, A.:  
Backjumping for quantified boolean logic satisfiability.  
In: IJCAI. (2001) 275–281



Zhang, L., Malik, S.:  
Conflict driven learning in a quantified boolean satisfiability  
solver.  
In: Proceedings of the 2002 IEEE/ACM international  
conference on Computer-aided design (ICCAD'02), New  
York, NY, USA, ACM (2002) 442–449



Benedetti, M.:  
Evaluating QBFs via symbolic Skolemization.  
In: 11th International Conference on Logic for  
Programming, Artificial Intelligence, and Reasoning  
(I PAR04) Number 3452 in LNCS



Biere, A.:

Resolve and expand.

In: Proceedings of 7th International Conference on Theory and Applications of Satisfiability Testing (SAT'04), Springer-Verlag (2004)



Benedetti, M.:

sKizzo: A QBF decision procedure based on propositional skolemization and symbolic reasoning.

Technical report, ITC-Irst (2004)



Tseytin, G.S.:

On the complexity of derivation in propositional calculus.

In: Studies in Constructive Mathematics and Mathematical Logic II. Volume 8 of Zapiski Nauchnykh Seminarov LOMI. Nauka, Leningrad (1968) 235–259 In Russian.



Giunchiglia, E., Narizzano, M., Tacchella, A.:  
QuBE: A system for deciding quantified boolean formulas  
satisfiability.

In: Proceedings of 1st International Joint Conference on  
Automated Reasoning (IJCAR'01). (2001) 364–369



Giunchiglia, E., Narizzano, M., Tacchella, A.:  
Quantified Boolean Formulas Satisfiability Library  
(QBFLIB) (2001) [www.qbflib.org](http://www.qbflib.org).



Peschiera, C., Pulina, L., Tacchella, A.:  
QBF solver evaluation portal  
<http://www.qbflib.org/qbfeval>.

# Thank you

## Question?