Solving bitvectors with MCSAT: explanations from bits and pieces

Stéphane Graham-Lengrand, Dejan Jovanović, Bruno Dutertre

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tl;dl (Too Long; Didn't Listen)

- MCSAT (Model-Constructing Satisfiability) is a scheme for SMT-solving (Satisfiability-Modulo-Theories), alternative to DPLL(T).
- To apply the scheme to a particular theory *T*, you need a form of *interpolation* mechanism for *T*.
- Designing an efficient mechanism for the full theory of bitvectors is difficult. So we do it for 2 fragments of the theory:
 - Equality + concatenation and extraction of bitvectors
 - A fragment of bitvector arithmetic

Outside these fragments we use a less efficient, but generic, procedure.

- ► The approach is implemented in SRI's SMT-solver Yices.
- ▶ We experimented it on the SMTLib benchmarks.

Overview of MCSAT

The bitvector theory in MCSAT

Experimentation on the SMTLib benchmarks

Conclusion

1. Overview of MCSAT

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The template is a generalisation of how CDCL works, the core calculus of SAT-solvers.

Run = alternation of search phases and conflict analysis phases

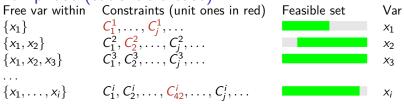
- Like CDCL's trail assigns Boolean values to Boolean variables, MCSAT's trail assigns
 - Boolean values to theory atoms; these constitute theory contraints
 - model values to first-order variables (e.g., $x \leftarrow 3/4$)

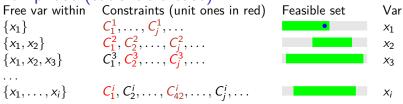
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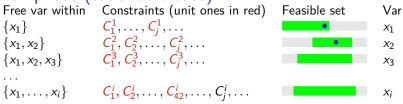
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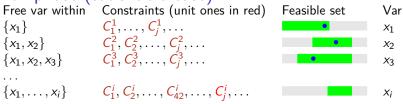
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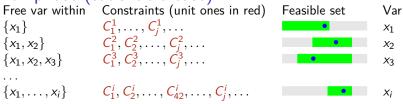
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- If all variables get values while maintaining invariant: SAT. illustration on the next slide.

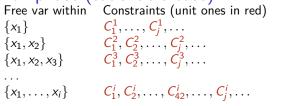








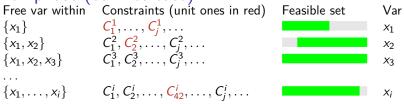


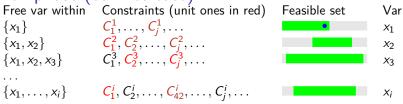


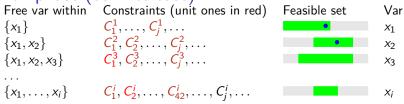


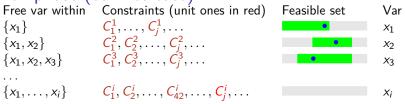
Xi

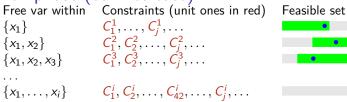
SAT











Conflict

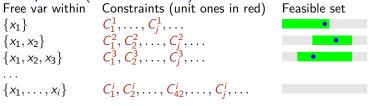
Var

 X_1

 X_2 X_3

Xi

•



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Var

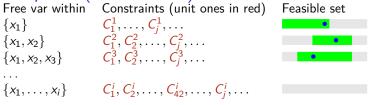
 X_1

Х2 Х3

 $x_i = y$

If at any point the invariant cannot be maintained, it means:

- Some variables x₁,..., x_n have already been assigned values v₁,..., v_n (here n = i−1): this constitutes a partial model M;
- No value can be assigned to y = x_i to extend M into a model of the constraints {C₁,..., C_m} unit in y: M falsifies ∃y(C₁ ∧ ··· ∧ C_m), denoted M ⊭ ∃yA, where A is C₁ ∧ ··· ∧ C_m.



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 X_1

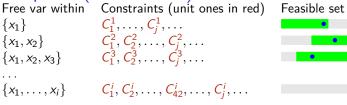
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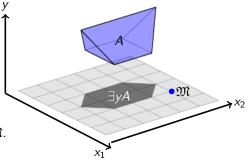
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To avoid picking the same values (i.e. the same \mathfrak{M}) or another model \mathfrak{M}' that fails "for the same reason" \mathfrak{M} fails, we generalise \mathfrak{M} into a class of failing models and characterise this class by a *conflict explanation*.

The conflict explanation is a quantifier-free *B* (with $fv(B) \subseteq \{\vec{x}\}$) over-approximating $\exists yA$:

• $\mathcal{T} \models (\exists yA) \Rightarrow B$ • $\mathfrak{M} \nvDash B$

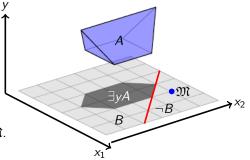
B is an *interpolant* of $\exists yA$ at \mathfrak{M} .

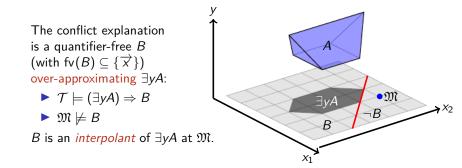


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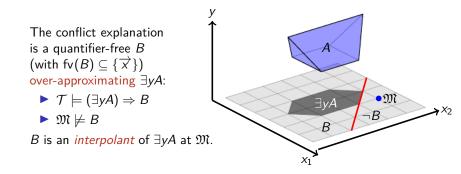
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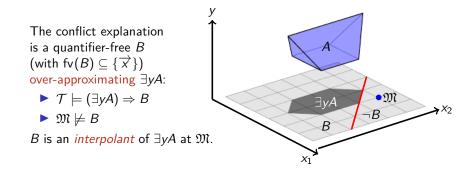


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It backtracks to a point where $A \Rightarrow B$ is no longer violated, e.g., *B* no longer evaluates (to false).

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MCSAT framework is implemented in **Yices** (SRI's main SMT-solver), with plugins for Boolean, non-linear arithmetic, EUF (can be mixed), ... and now bitvectors.

2. The bitvector theory in MCSAT

Bitvectors

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On the whole SMTlib bitvector benchmarks, MCSAT does not perform as well as long established bitblasting solvers (comparison later in this talk), but there is a decent subset of instances where it performs better...

A trivial example

```
(set-info :smt-lib-version 2.6)
(set-logic QF BV)
(set-info :source |
We verify that (x < y) \rightarrow (x + 1 \le y)
. . .
1)
(set-info :status unsat)
(declare-fun x () (_ BitVec 29980))
(declare-fun y () (_ BitVec 29980))
(assert (bvult x y))
(assert (bvugt (bvadd x (_ bv1 29980)) y))
(check-sat)
(exit)
```

The best 2 solvers of the SMT-comp 2019 (which use bitblasting) cannot solve this.

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Updating the set of feasible values when a constraint becomes unit corresponds to computing a conjunction of 2 BDDs.

We need an explanation mechanism producing clausal interpolants (satisfying some suitable conditions for termination – easy here);

If $\exists y (C_1 \land \dots \land C_m)$ evaluates to false in $\mathfrak{M} = \{x_1 \leftarrow v_1, \dots, x_n \leftarrow v_n\}$ (i.e., if v_1, \dots, v_n are the values picked for x_1, \dots, x_n , and C_1, \dots, C_m are the constraints that leave no feasible values for y)

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Default explanation mechanism:

Bitblast the unsat formula $C_1 \wedge \cdots \wedge C_m \wedge x_1 \simeq v_1 \wedge \cdots \wedge x_n \simeq v_n$, and get an *unsat core* identifying the bits of x_1, \ldots, x_n that mattered.

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Better than the naive mechanism, but still inefficient: Many bit-level explanations may be needed to capture a property that could be expressed at the word level.

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- we aggressively rewrite the remaining constraints...
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The fragments:

- Equality with concat + extract
- A fragment of linear bitvector arithmetic

Equality with concat + extract

Constraints $C ::= t \simeq t \mid t \not\simeq t$ Terms $t ::= e \mid y[h:l] \mid t \circ t$

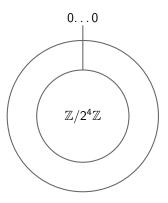
where *e* ranges over *evaluable terms*, i.e., terms without variable *y* (their free variables x_1, \ldots, x_n have values in the current model \mathfrak{M})

Equality with concat + extract

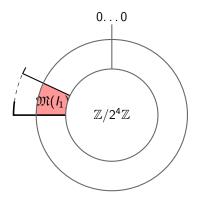
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Explanation mechanism given in the paper, utilising *slicing* and model-aware E-graph.

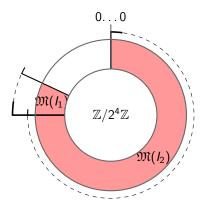
 $\mathfrak{M} = \{x_1 \leftarrow 1100, x_2 \leftarrow 1101, x_3 \leftarrow 0000\}$ Constraint $C_1: \neg (y \simeq x_1)$ Constraint $C_2: (x_1 \leq^u x_3 + y)$ Constraint $C_3: \neg (y - x_2 \leq^u x_3 + y)$



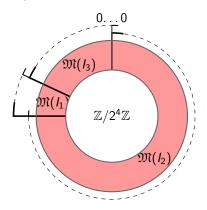
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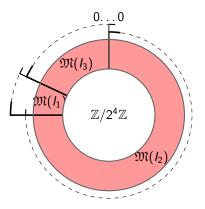


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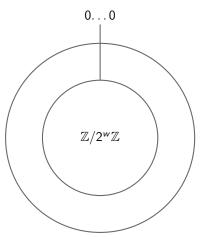
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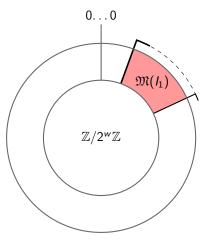
Space of values for *y* (feasible ones in white, forbidden ones in red):

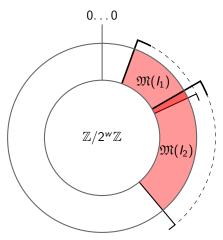


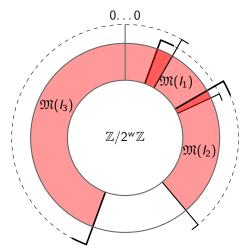
The explanation is $(x_1+1) \in I_3 \land (-x_3) \in I_2 \land (x_1-x_3) \in I_1$

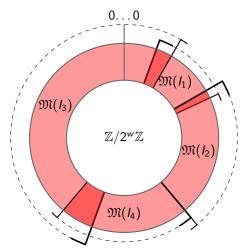
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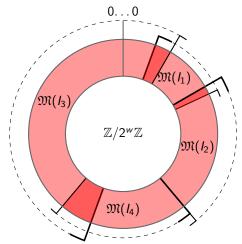






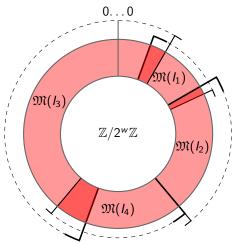


Each constraint C_i forbids an interval I_i with interpretation $\mathfrak{M}(I_i)$ and upper bound u_i .



All values in $\mathbb{Z}/2^w\mathbb{Z}$ end up being forbidden because: $\mathfrak{M}(u_1) \in \mathfrak{M}(l_2)$ and $\mathfrak{M}(u_2) \in \mathfrak{M}(l_4)$ and $\mathfrak{M}(u_4) \in \mathfrak{M}(l_3)$ and $\mathfrak{M}(u_3) \in \mathfrak{M}(l_1)$

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18/32

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From the set {*I*₁,..., *I_m*} of intervals corresponding to constraints *C*₁,..., *C_m*,
 extract a sequence *I_{π(1)}*,..., *I_{π(q)}* covering Z/2^wZ in model M, two consecutive intervals being hooked together.

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► Express constraints "a ∈ [d; u[" in the language of linear bv-arithmetic: a−d <^u u−d In the example, the explanation

$$(x_1+1) \in I_3 \land (-x_3) \in I_2 \land (x_1-x_3) \in I_1$$

is expressed as

$$(x_1+1-x_2 <^u -x_3-x_2) \land (0 <^u x_1) \land (-x_3 <^u 1)$$

The 12 cases of constraints turning into forbidden intervals capture the following grammar:

Constraints $C ::= a \mid \neg a$ Atoms $a ::= e_1 + y \leq^u e_2 + y \mid e_1 \leq^u e_2 + y \mid e_1 + y \leq^u e_2$

where e_1, e_2 range over *evaluable terms*.

We can extend the grammar into:

Constraints $C ::= a \mid \neg a$ Atoms $a ::= e_1 + t \leq^u e_2 + t \mid e_1 \leq^u e_2 + t \mid e_1 + t \leq^u e_2$ Terms t ::= y[h:]

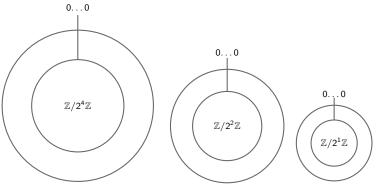
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Generalization 1: with lower-bit extraction, leading to multiple bitwidths that the technique has to support (Algorithm 3 in the paper).

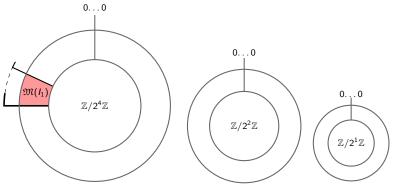


20/32

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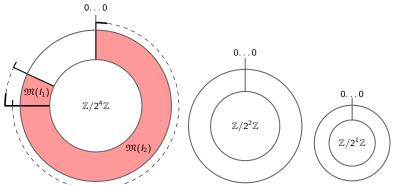


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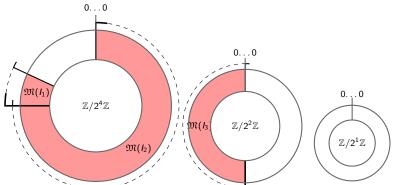


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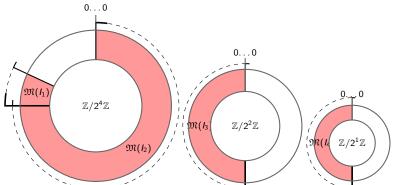
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Generalization 2:

also with nestings of upper-bit extraction, addition of evaluable terms, negation, and concatenations with 0s (or with evaluable terms). See Figure 1 in the paper.

Extending the method - by adding rewrites

We normalise the constraints in the conflict with the following rules (Figure 3 in the paper):

$ \begin{array}{cccc} u_1 <^s u_2 & \rightsquigarrow \neg (u_2 \leq^s u_1) \\ u_1 <^u u_2 & \rightsquigarrow \neg (u_2 \leq^u u_1) \end{array} $	$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$\begin{array}{c} u[:l][h] \rightsquigarrow u[h+l:][:l] & \text{if } h \leq u_2 \\ (u_1 \circ u_2)[h] \rightsquigarrow u_2[h] & \text{if } h \leq u_2 \\ (u_1 \circ u_2)[h] \implies u_1[h- u_2 :] \circ u_2 & \text{if not} \\ (u_1+u_2)[h:] \rightsquigarrow u_1[h:] + u_2[h:] \\ (u_1 \times u_2)[h:] \rightsquigarrow u_1[h:] \times u_2[h:] \\ (-u)[h:] \rightsquigarrow -u[h:] \end{array}$	

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$u_1 <_{}^{s} u_2$	$\rightsquigarrow \neg (u_2 \leq^s u_1)$		$u_1 \leq^{s} u_2 \rightsquigarrow u_1 + 2^{ u_1 - 1} \leq^{u} u_2 + 2^{ u_2 - 1}$		
$u_1 <^{u} u_2$	$\rightsquigarrow \neg(u_2 \leq^u u_1)$		$u_1 \simeq u_2 \rightsquigarrow u_1 - u_2 \leq^u 0$		
u[h:/]	→ u[h:][:1]		$u[:I][h:] \rightsquigarrow u[h+I:][:I]$		
$(u_1 \circ u_2)[:I]$	$\rightarrow u_1[:I- u_2]$	if $ u_2 \leq I$	$(u_1 \circ u_2)[h:] \rightsquigarrow u_2[h:]$	if $h \leq u_2 $	
$(u_1 \circ u_2)[:I]$	$\rightarrow u_1 \circ u_2[:I]$	if not	$(u_1 \circ u_2)[h:] \rightsquigarrow u_1[h- u_2 :] \circ u_2$	if not	
$2^n \times u$	$\rightsquigarrow u[u -n:] \circ 0_n$	(n < u)	$(u_1+u_2)[h:] \rightsquigarrow u_1[h:] + u_2[h:]$		
bvnot(u)	$\rightarrow -(u+1)$		$(u_1 \times u_2)[h:] \rightsquigarrow u_1[h:] \times u_2[h:]$		
$\pm \operatorname{-extend}_k(u) \rightsquigarrow (0_k \circ (u+2^{ u -1})) - (0_k \circ 2^{ u -1})$		$(-u)[h:] \rightsquigarrow -u[h:]$			
$u_1 \circ u_2$	$\rightarrow (u_1 \circ 0_{ u_2 }) + (0)$	$ u_1 ^{\circ u_2}$)	· · · · · ·		

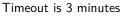
This allows the plugin to cover (at least) the following grammar:

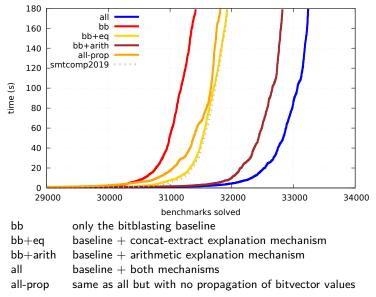
Atoms $a ::= e_1 + t < e_2 + t | e_1 < e_2 + t | e_1 + t < e_2 | e_1 < e_2$ Terms $t ::= t[h:l] | t + e_1 | -t | e_1 \circ t | t \circ e_1 | \pm \text{-extend}_k(t)$ where < is any comparison symbol in $\{\leq^u, <^u, \leq^s, <^s, \simeq\}$, and terms can also involve arbitrary extracts, sign-extensions, etc

3. Experimentation on the SMTLib benchmarks

Effects of explanation mechanisms and propagation

 \ldots on the 41,547 instances in SMTLib (QF_BV)





23/32

Numbers

Total number of instances solved by all: 33,236 (14,174 solved by pure preprocessing + 19,062 using MCSAT)

- ▶ 14,313 are solved without ever calling the default bitblasting baseline (~ half of the benchmarks are entirely within the two fragments)
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MCSAT not as good on the whole, but in the paper we identify classes of instances where MCSAT is better, e.g., arithmetic explanation mechanism is insensitive to big bitwidths. For instance, MCSAT could solve 794 instances for which Boolector+CadiCal timed out.

4. Conclusion

Related work

MCSAT approach to bitvectors first explored in [ZWR16], using

- bitvector intervals and masks to represent domains;
- eager propagation mechanisms instead of interpolation-based conflict-explanations.

Our numbers on SMTLib seem to improve on [ZWR16] quite a bit.

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Our numbers on SMTLib seem to improve on [ZWR16] quite a bit.

Our work extends preliminary work [GLJ17, GLJ19]. Main improvements:

- Use of arbitrary evaluable terms to extend the scopes of the 2 fragments;
- Generalization 2 of the arithmetic explanation mechanism;
- Normalization of conflicts by rewrite rules
- Experimentation

Future work and MCSAT beyond ground SMT-solving

Extend the fragments little by little, e.g., handling a bigger fragment of bitvector arithmetic, e.g., with arbitrary coefficients for the conflict variable y in polynomials.

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- Extend the fragments little by little, e.g., handling a bigger fragment of bitvector arithmetic, e.g., with arbitrary coefficients for the conflict variable y in polynomials.
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 - invertibility conditions [NPR⁺18]
 - other techniques inspired by *quantifier elimination*, e.g., [JC16]

Even if MCSAT ends up not performing as well as bitblasting on ground instances, it may still be interesting to produce word-level explanations of conflicts.

Two applications of these MCSAT explanations currently investigated at SRI:

- General interpolation problems in the bitvector theory
- Solving *quantified problems* in the bitvector theory

Questions?

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