Machine Learning for Quantifiers

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Outline

Intro: QBF, Expansion, Games, Careful expansion

Solving QBF

Learning in QBF

Targeting SMT

Towards Synthesizing Terms

Towards Infinite Models

Careful expansion

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```
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4 1 (True)

Satisfiability Modulo Theories (SMT)

Example (single instantiations)

$$f: \mathbb{Z} \to \mathbb{Z}$$

$$(\forall x: \mathbb{Z})(f(x) > 0)$$

$$f(0) < 0$$

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• Example (many instantiations)

$$f : \mathbb{Z} \to \mathbb{Z}$$

$$(\forall x : \mathbb{Z})(f(x) < f(x+1))$$

$$f(0) > f(100)$$

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 \exists -player wins by playing $e \triangleq u$.

Solving QBF

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Observe:

• $(\exists x \forall uzw)((u \land z \land w) \Rightarrow x) \land ((\neg u \land \neg z \land \neg w) \Rightarrow \neg x)$

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- What is a good expansion?

$$(\exists \vec{E} \, \forall \vec{U}) \, \phi \equiv (\exists \vec{E}) \, \bigwedge_{\mu \in 2^{\vec{U}}} \phi[\mu]$$

Expand gradually instead: [J. and Marques-Silva, 2011]

• Pick au_0 arbitrary assignment to $ec{\it E}$

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- After *n* iterations

$$(\exists \vec{E}) \bigwedge_{i \in 1...n} \phi[\tau_i]$$

Strengths and Weaknesses



Careful Expansion: Good Example

$$(\exists x \dots \forall y \dots)(\phi \land y)$$

Setting counter-move $y \triangleq 0$ yields false. Stop.

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$$(\exists x \dots \forall y \dots)(x \vee \phi)$$

Setting candidate $x \triangleq 1$ yields true. Stop.

Careful Expansion: Bad Example

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Necessarily you need to use both:

$$SAT(x \Leftrightarrow 0 \land x \Leftrightarrow 1) \dots UNSAT$$

Stop

Careful Expansion: Ugly Example

$$(\exists x_1x_2\forall y_1y_2)(x_1 \Leftrightarrow y_1 \vee x_2 \Leftrightarrow y_2)$$

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Necessarily need 2^2 values of y_1, y_2

Learning in QBF

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- Idea: plug in functions rather than constants.
- · Where do we get the functions?

[J., 2018]

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- 4. Repeat.

<i>x</i> ₁	<i>x</i> ₂	 x _n	<i>y</i> ₁	<i>y</i> ₂	 Уn
0	0	 0	1	1	 1
1	0	 0	0	1	 1
0	0	 1	1	1	 0
0	1	 1	1	0	 0

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- After 4 steps: $y_1 \leftarrow \neg x_1 \ y_2 \leftarrow \neg x_2 \dots$

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- After 4 steps: $y_1 \leftarrow \neg x_1 \ y_2 \leftarrow \neg x_2 \dots$
- Eventually we learn the right functions.

• Use CEGAR as before.

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- Recursion to generalize to multiple levels as before.

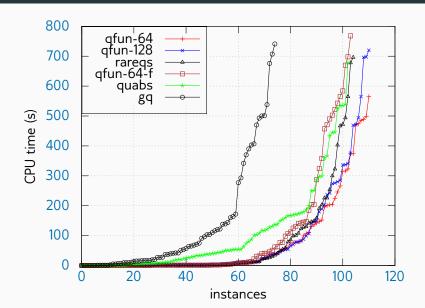
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- · Refinement as before.
- Every K refinements, learn new functions from last K samples.
 Refine with them.
- Learning using decision trees by ID3 algorithm.
- Additional heuristic: If a learned function still works, keep it.
 "Don't fix what ain't broke."

Experiments



Targeting SMT

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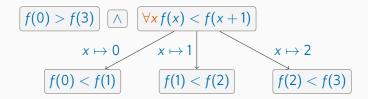
Instantiation:

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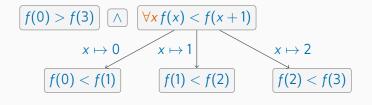
 $\land f(c) = c$
 $\land f(f(c)) = f(c)$

Instantiations for UnSAT

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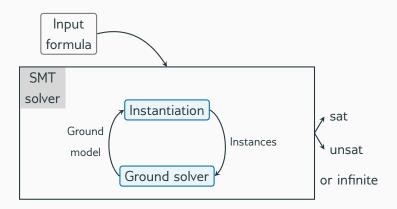


Instantiations for UnSAT

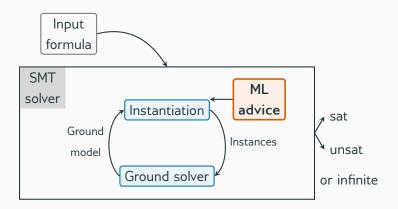




Setup for Machine Learning

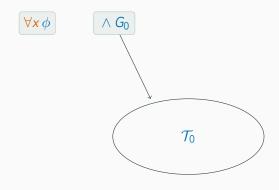


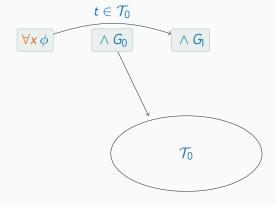
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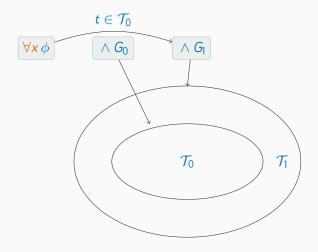


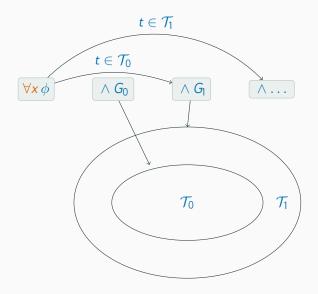












 \forall x y z $(x < y) \lor (x < z)$

\forall	Χ	у	Z	$(x < y) \lor (x < z)$
	0	1	11	
	3	5	7	
	10	9	2	

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Set of terms for quantified variable

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Objective:

Order the terms to increase likelihood of UnSAT

[J. et al., 2022]

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- Learned forest gives a score to each ground term.

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 - · term context

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 - depth
 - tried
 - · term context
 - variable context

- bag-of-words (BOW) features:
 - kinds determined by AST in cvc5: variable, skolem, not, and, plus, forall, etc.
 - count number of occurrences of a symbol
 - for example: $BOW(\forall x \, 2 + x = skl_1 + 3) = \{forall : 1, variable: 1, const : 2, skolem : 1, plus : 2\}$
- · additional features:
 - age
 - phase
 - depth
 - tried
 - · term context
 - variable context
 - variable frequency

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 - 4. Go to Step 1.

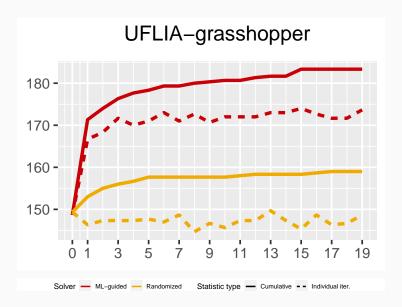
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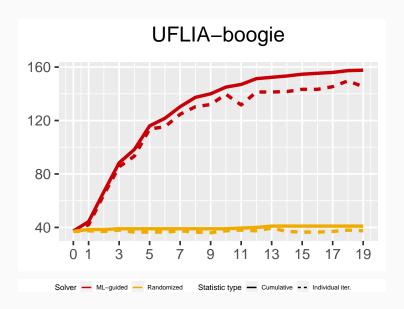
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- Single-Instantiation Goal

Solved instances - Target set

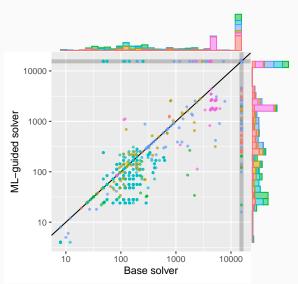


Solved instances - Target set



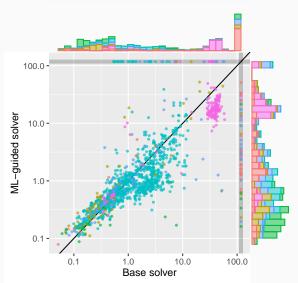
Holdout Set: Instantiation Count

Instantiations



Holdout Set: Time Comparison



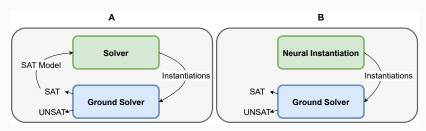


Towards Synthesizing Terms

ML Maximalist — Proving By Instantiation

[Piepenbrock et al., 2025]

- A GNN analyzes the formula, and predicts how to instantiate clauses by growing terms
- SAT solver (+ congruence closure) does the rest



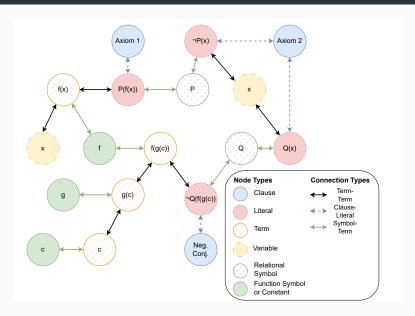
Synthesizing Terms

- (1) instantiate x by head symbol h with arity 2 and z by g of arity 1 (going from level₀ to level₁)
- (2) instantiate x_1, x_2, z_1 by constants c, c, and e, respectively (going from level₁ to level₂)

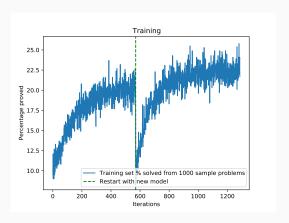
Synthesizing Terms by GNN2RNN

$$\forall xz. P(f(x,z)) \\ \forall x_1x_2z_1. P(f(h(x_1,x_2),g(z_1))) \\ P(f(h(c,c),g(e))) \\ \xrightarrow{\text{GNN}} x: h \quad z: g \\ \underset{\text{RNN}}{x_1: c} \underbrace{x_2: c}_{\text{RNN}} z: e$$

GNN Example



System Can Learn



Dedicated Provers are Still Better

Table 1: Performance of various methods. iProver is used in pure instantiation mode. Random is 1 run of the 2-level random grounding. In parentheses, we indicate which dataset was used.

Time limit	1s	10s	60s	Inst. + 30s
Random (all)	_	_	_	3.44%
Neural (train)	_	_	_	26.25%
Neural (test)	_	_	_	19.74%
iProver (train)	43.28%	59.99%	67.6%	_
iProver (test)	43.16%	59.75%	68.69%	_
CVC5 (test)	83.44%	85.6%	86.28%	_

Towards Infinite Models

SMT Models: Constants

```
(declare-fun c () Int)
(declare-fun d () Int)
(assert (< c d))
(check-sat)
(get-model)</pre>
```

c < d

SMT Models: Constants

```
(declare-fun c () Int)
(declare-fun d () Int)
(assert (< c d))
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```

```
:!z3 ex1.smt2
sat
(
   (define-fun d () Int
    1)
   (define-fun c () Int
    0)
)
```

SMT Models: Functions

```
(declare-fun f (Int) Int)
(assert (< (f 0) (f 1)))
(check-sat)
(get-model)</pre>
```

f(0) < f(1)

SMT Models: Functions

```
(declare-fun f (Int) Int)
(assert (< (f 0) (f 1)))
(check-sat)
(get-model)</pre>
```

f(0) < f(1)

```
:!z3 ex2.smt2
sat
(
   (define-fun f ((x!0 Int)) Int
        (ite (= x!0 1) 1
            0))
)
```

```
fx \triangleq (1 \text{ if } x = 1 \text{ else } 0)
```

```
fx \triangleq x
```

```
:!z3 -T:60 ex4.smt2
timeout
```

Not Solved!

Learn infinite models from finite ones?

For $\forall x \phi$ construct a sequence of:

• candidate models M_i

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$$(\forall x)(fx > x)$$

$$\bigwedge_{j \in 1..i-1} \phi[x/\sigma_j] \qquad M_i \qquad \sigma_i$$

$$true \qquad fx \triangleq 0 \qquad x \mapsto 0$$

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$$\bigwedge_{j\in 1..i-1} \phi[x/\sigma_j]$$

 M_i

 σ_i

$$(\forall x)(fx > x)$$

$$\bigwedge_{j \in 1..i-1} \phi[x/\sigma_j] \qquad M_i \qquad \sigma_i$$

$$f(0) > 0 \qquad fx \triangleq 1 \qquad x \mapsto 1$$

$$(\forall x)(fx > x)$$

 σ_i

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$$\frac{\bigwedge_{j\in 1..i-1} \phi[x/\sigma_j]}{f(0) > 0}$$

 M_i

 σ_i

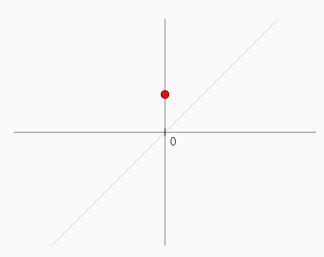
 $fx \triangleq (x = 0.71)$ (x = 1?2:3)





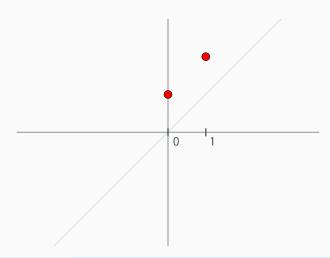
Example: Generalization





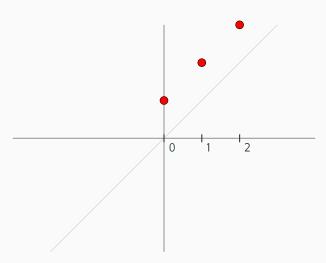
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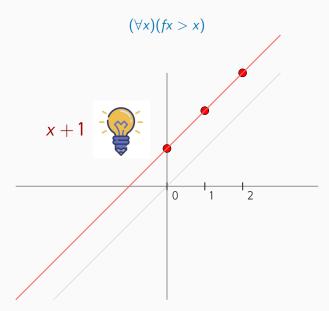


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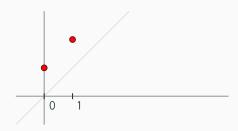
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- Keep the same hyper-plane as long as possible
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- For LIA: linear Diophantine equations, solvable in polynomial time

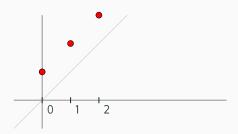
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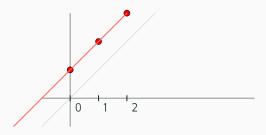
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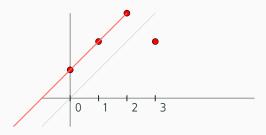
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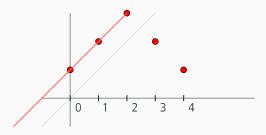
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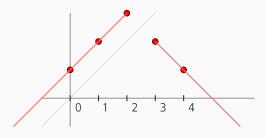
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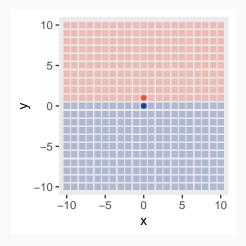


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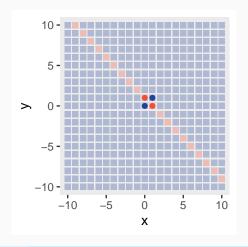


- Split recursively by hyper-planes
- until all positive or all negative

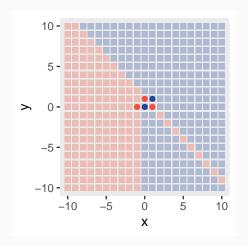
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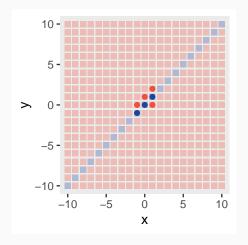
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Results UFLIA

- Implemented in cvc5
- Run on [J. et al., 2023]

solver	SAT	UNSAT	total
standard MBQI	18,843	7,863	26,706
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ours smart MBQI	31,977	7,863	39,840
Z3	28,380	7,482	35,862

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 It might be useful to instantiate by more complicated objects,
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- In SMT instantiations can be ordered by ML.
- Synthesizing new terms is possible, but harder.
- Synthesizing new models is also possible but What are the appropriate ML techniques?



Towards generalization in QBF solving via machine learning.

[in M., Brown, C. E., and Kaliszyk, C. (2023).

A benchmark for infinite models in SMT.

[i] J., M. and Marques-Silva, J. (2011).

Abstraction-based algorithm for 2QBF.

[in J., M., Piepenbrock, J., and Piotrowski, B. (2022).

Towards learning quantifier instantiation in SMT.

Piepenbrock, J., Urban, J., Korovin, K., Olšák, M., Heskes, T., and J., M. (2025).

Invariant neural architecture for learning term synthesis in instantiation proving.