

Chronosymbolic Learning

Efficient CHC Solving with Symbolic Reasoning and Inductive Learning

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Table of Contents

- 1 What is CHC & Why CHC
- 2 Existing Approaches on Solving CHCs
- 3 Chronosymbolic Learning

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- 2 Existing Approaches on Solving CHCs
- 3 Chronosymbolic Learning

Constraints like this can be solved by *SMT solvers*:

$$\forall a, b, c, a > 0 \wedge b \leq a \wedge c = 0 \rightarrow a + b + c \geq 0$$

- It is **SAT** iff for all assignments of (a, b, c) , the constraint holds
- It is **UNSAT** iff for some assignments, the constraint does not hold
- Logical implication: $p \rightarrow q \triangleq \neg p \vee q$

One step further: Predicate

How about this?

$$\forall a, b, c, a > 0 \wedge b \leq a \wedge c = 0 \rightarrow p(a, b, c)$$

- $p(x, y, z)$: an unknown predicate that maps variables to True/False
- Example: $p(x, y, z) = x < y$
- It is **SAT** iff there exist an *interpretation* of p that makes the constraint holds for all assignments of (a, b, c)
- It is **UNSAT** iff there is no such *interpretation* of p that makes the constraint holds for all assignments of (a, b, c)
- A logical implication with unknown predicate is called a **Constrained Horn Clause (CHC)**

Constrained Horn Clause System

How about a *system* of such constraints?

$$\mathcal{C}_0 : \forall a, b, c, \ a > 0 \wedge b \leq a \wedge c = 0 \rightarrow p(a, b, c)$$

$$\mathcal{C}_1 : \forall a, b, c, c_1, \ c_1 = 1 + c \wedge p(a, b, c) \rightarrow q(a, b, c_1)$$

$$\mathcal{C}_2 : \forall a, b, c, \ b < a \cdot c \wedge q(a, b, c) \rightarrow \perp$$

- It is **SAT** iff there exist an *interpretation* of all predicates (p, q) that makes all constraints SAT
- It is **UNSAT** iff there is no such *interpretation* that makes all constraints SAT

CHCs and Formal Verification

$$x = 1 \wedge y = 0 \rightarrow p(x, y) \quad (1)$$

$$p(x, y) \wedge x' = x + y \wedge y' = y + 1 \rightarrow p(x', y') \quad (2)$$

$$p(x, y) \wedge x' = x + y \wedge y' = y + 1 \rightarrow x' \geq y' \quad (3)$$

$$x = 1 \wedge y = 0 \rightarrow x \geq y \quad (4)$$

```
main() {  
  int x, y;  
  x=1; y=0;   Some  
  while (*) { nondeterministic  
    x=x+y;    expression of x, y  
    y++; }  
  assert (x>=y) ; }
```

CHC is the *universal format* for formal verification!

- Can represent *any programming languages* and *any correctness specifications*
- Satisfiability of CHCs \Leftrightarrow Correctness of a program
- A program \Rightarrow CHCs can be automated

Table of Contents

- 1 What is CHC & Why CHC
- 2 Existing Approaches on Solving CHCs
- 3 Chronosymbolic Learning

Symbolic Reasoning-based CHC Solving

Symbolic reasoning-based CHC solvers solve CHCs by an organized way of (heuristic-guided) SMT solving

- Efficient: no need to collect data, many years of heuristic tuning
- Often focusing more on reasoning local information

Solving CHCs by data-driven approaches

Collecting data points for variables from “executing the program”

- Directly learns interpretations by induction learning
- Teacher and Learner paradigm, “Guess-and-check”
- Can take global information into account, but some cheap prior knowledge in CHC systems is ignored; Guess-and-check is slow

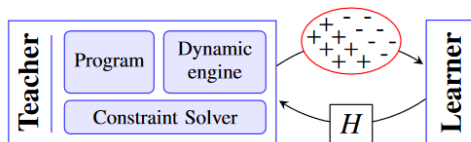


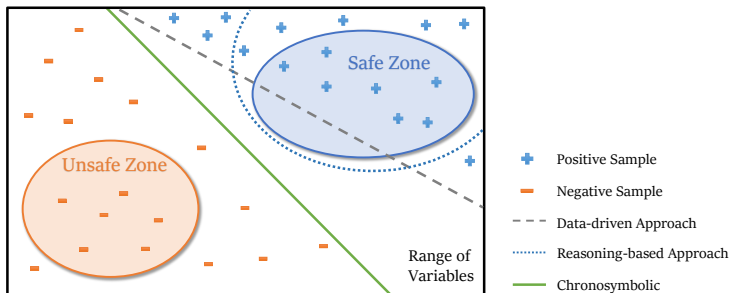
Table of Contents

- 1 What is CHC & Why CHC
- 2 Existing Approaches on Solving CHCs
- 3 Chronosymbolic Learning**

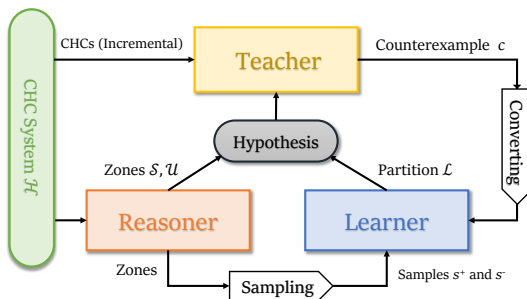
Chronosymbolic Learning

Can we rethink these two distinct methods into one unified framework?

- Partial solutions of reasoning are represented by *zones*
- Data *samples* are classified by binary classifier
- Making *Chronosymbolic* hypothesis $\tilde{\mathcal{I}}_{slu}[p_i] = \mathcal{S}_{p_i} \vee (\mathcal{L}_{p_i} \wedge \neg \mathcal{U}_{p_i})$



Chronosymbolic Learning



Architecture of *Chronosymbolic Learning*