

Satisfiability Modulo Theories : Beyond Decision Procedures

Andrew Reynolds

May 20, 2015

SMT Solvers for Software Verification/Security

Program

```
char buff[15], pass;
cout << "Enter the password :";
gets(buff);
if (regex_match(buff, std::regex("[A-Z]+"))) {
    if (strcmp(buff, "PASSWORD")) {
        cout << "Wrong Password";
    } else {
        cout << "Correct Password";
        pass = 'Y';
    }
}
if (pass == 'Y')
    /* Grant the root permission*/
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+ Property P

Does
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SMT
solver

YES

NO

SMT Solvers for Software Verification/Security

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SMT
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YES

NO

What kind
of properties
can we ask
about?


How do we
solve them?

Overview

- Satisfiability Modulo Theories (SMT) Solvers
 - Propositional reasoning, via off-the-shelf SAT solver
 - **Decision Procedures** for *theories*:
 - UF, Arithmetic, BitVectors, Arrays, ...
 - (Co)inductive Datatypes
 - ...also support **Undecidable Theories**:
 - Unbounded Strings + Length Constraints
 - ...and even arbitrary **Quantified Formulas**:
 - Finite Model Finding

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Focus of this talk,
my work in **CVC4**

What is a Theory?

- A *theory* T is a pair
 - A signature Σ_T containing sorts and function symbols
 - A class of models I_T describing the intended interpretations of symbols in Σ_T
- For example, linear integer arithmetic (LIA):
 - Σ_{LIA} contains functions $\{ +, -, <, \leq, >, \geq, 0, 1, 2, 3, \dots \}$
 - Each $I \in I_{LIA}$ interpret functions in Σ_{LIA} in standard way:
 - $1+1 = 2, 1+2 = 3, \dots, 1 > 0 = \text{true}, 0 > 1 = \text{false}, \dots$
- Number of widely-supported theories in SMT:
 - Bitvectors : `bvsgt (a, #bin0001)`
 - Arrays : `select (store (a, 5, b), c) = 5`
 - Datatypes : `tail (cons (a, b)) = b`
 - ...

What is a Decision Procedure for T?

- Input: a set of T-constraints M , under some syntactic restriction
- A decision procedure is a method that **terminates** with output:
 - “ M is T-satisfiable”, i.e. there is a solution
 - “ M is T-unsatisfiable”

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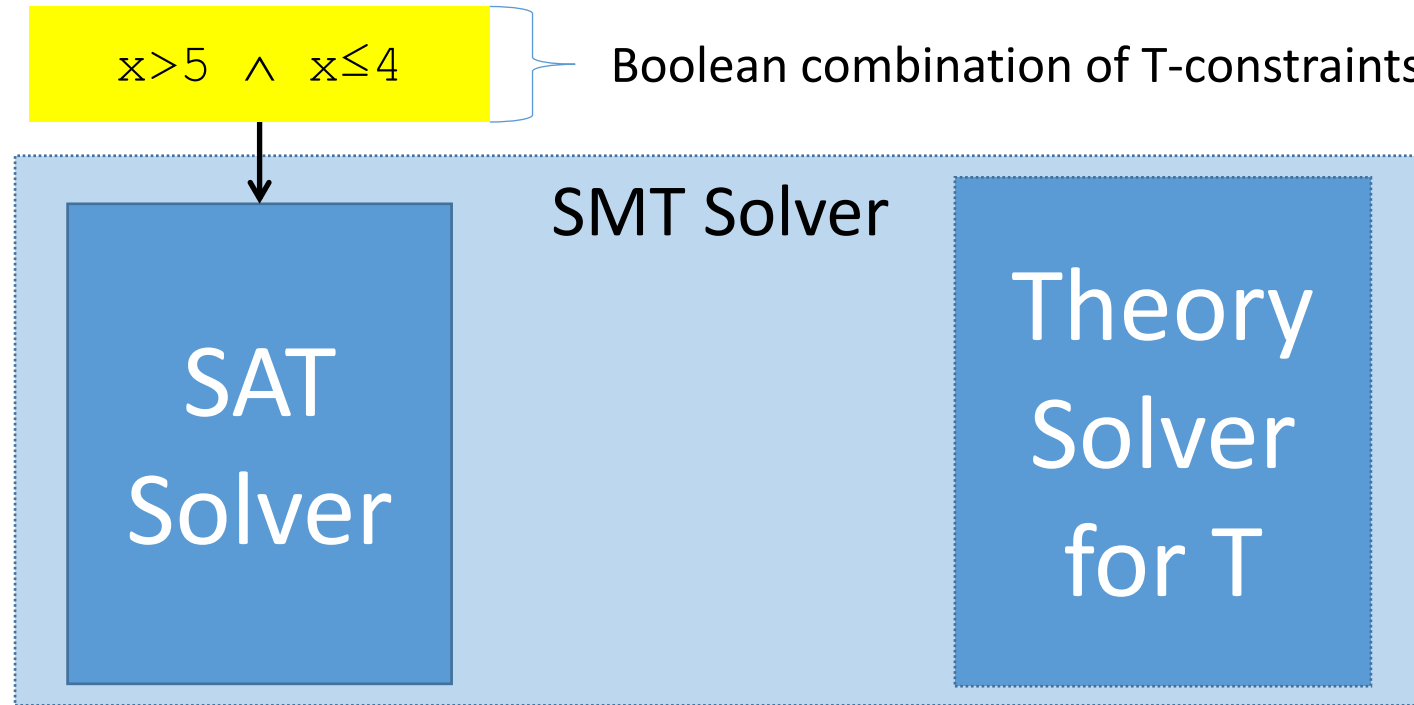
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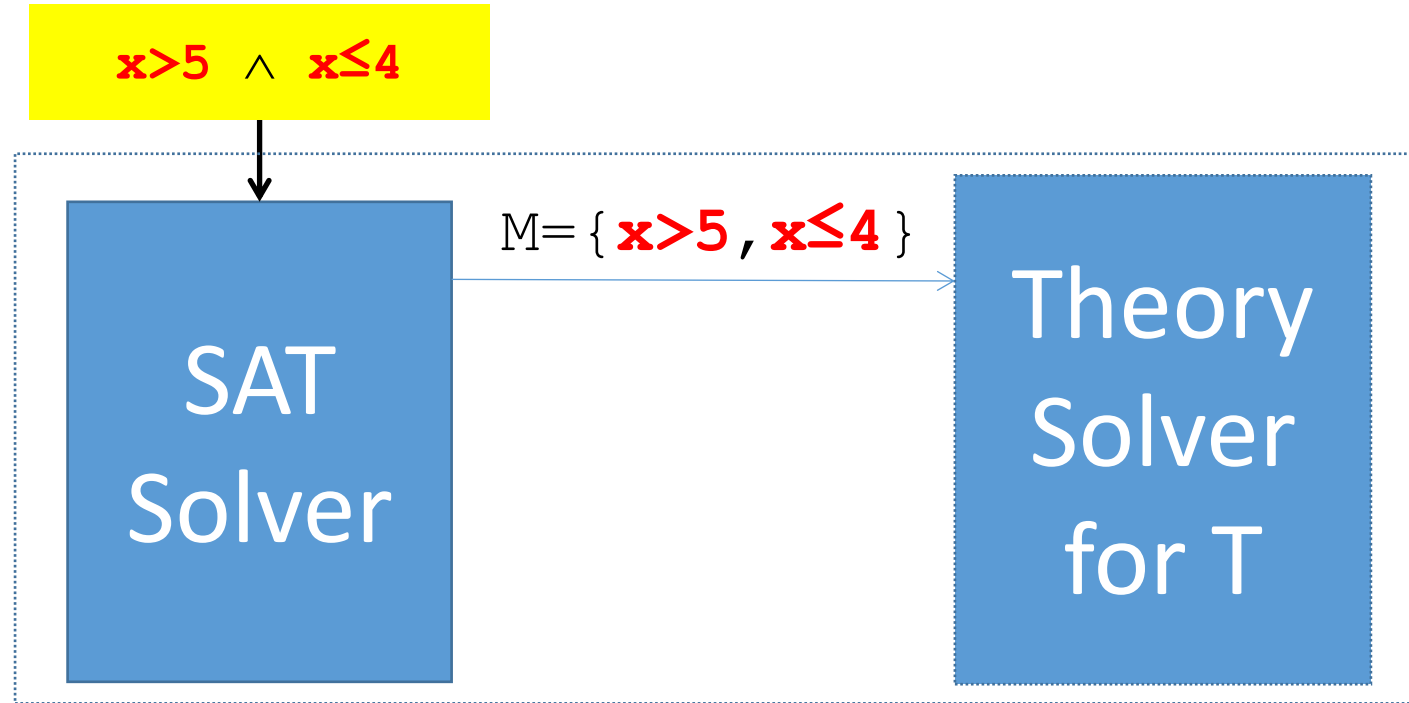
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 - Must be **refutation-sound**, returns “ M is T-unsatisfiable” only when M is T-unsatisfiable

How are Decision Procedures Implemented in SMT?



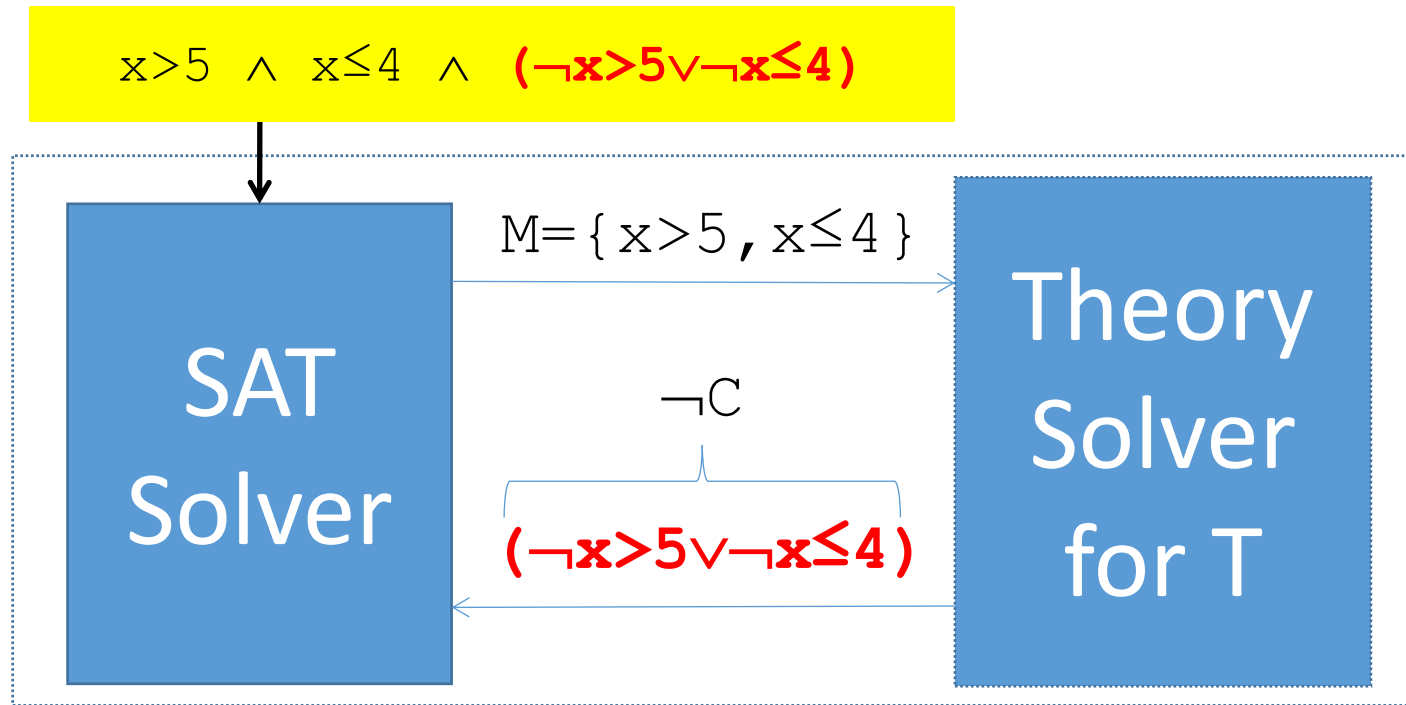
- Decision Procedures are implemented as *theory solvers*

How are Decision Procedures Implemented in SMT?



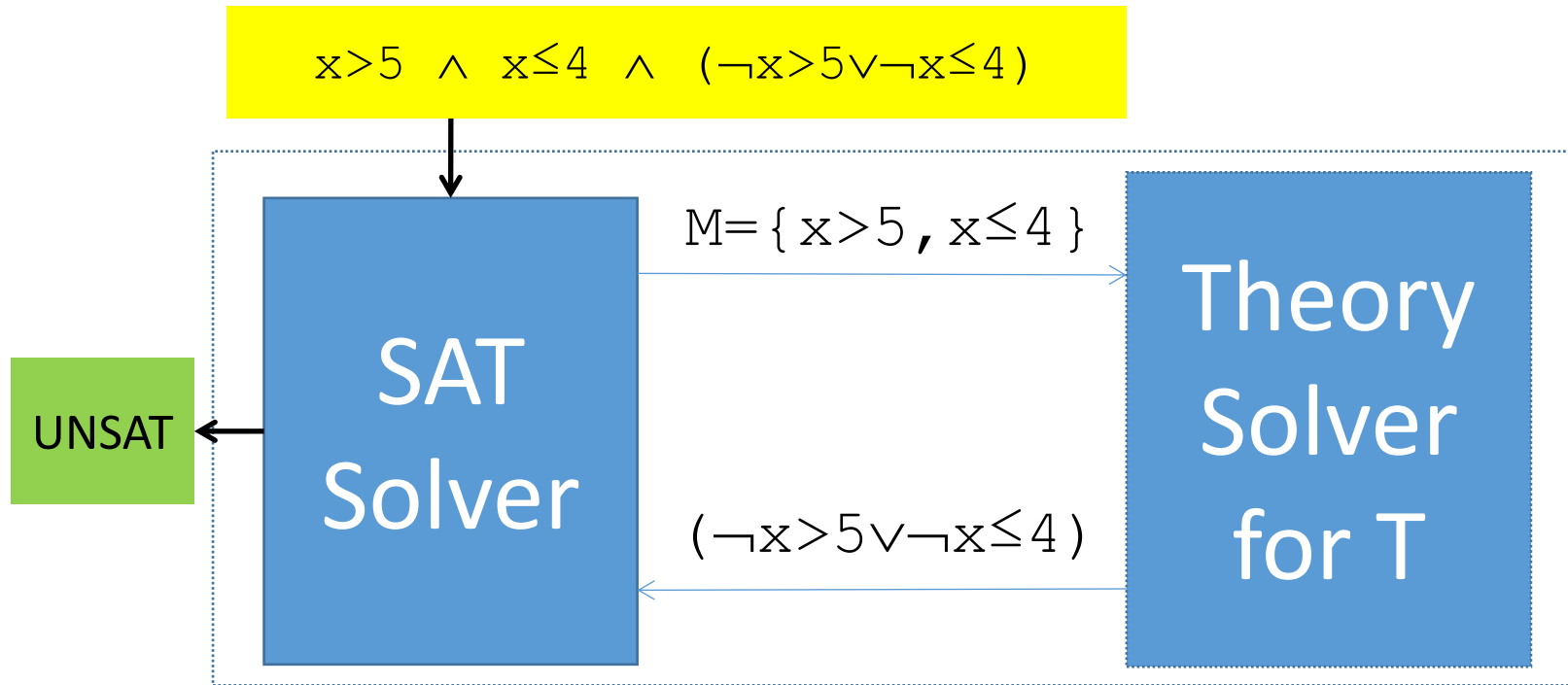
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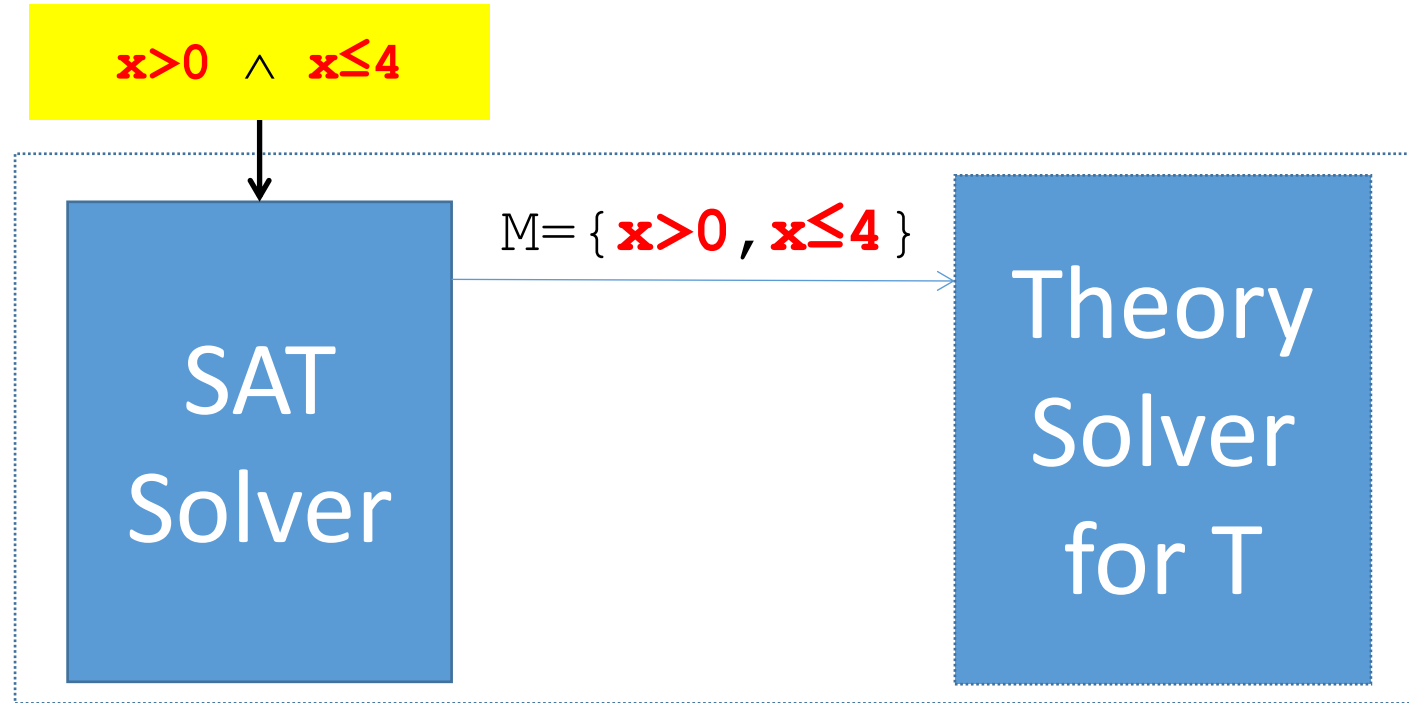
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- If M is T-unsat, find an inconsistent subset $C \subseteq M$, add **conflict** clause $\neg C$

How are Decision Procedures Implemented in SMT?



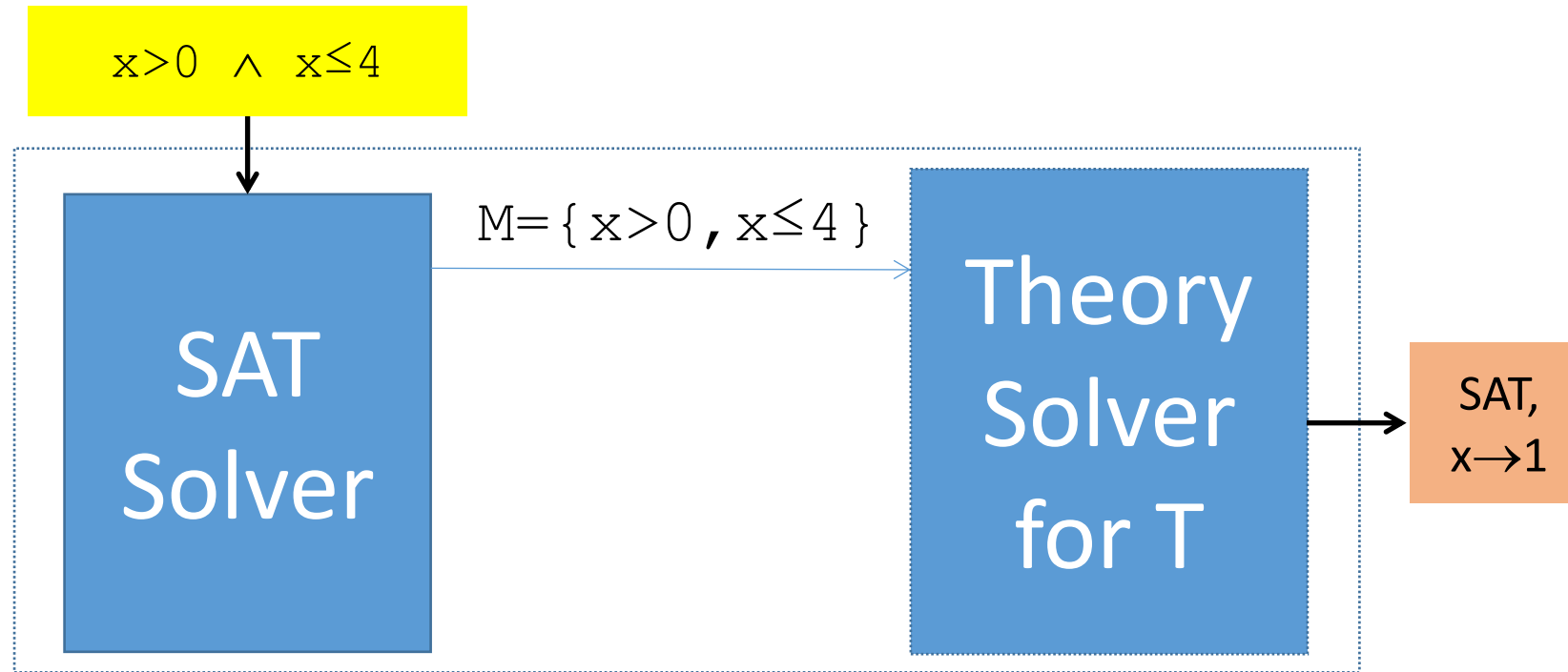
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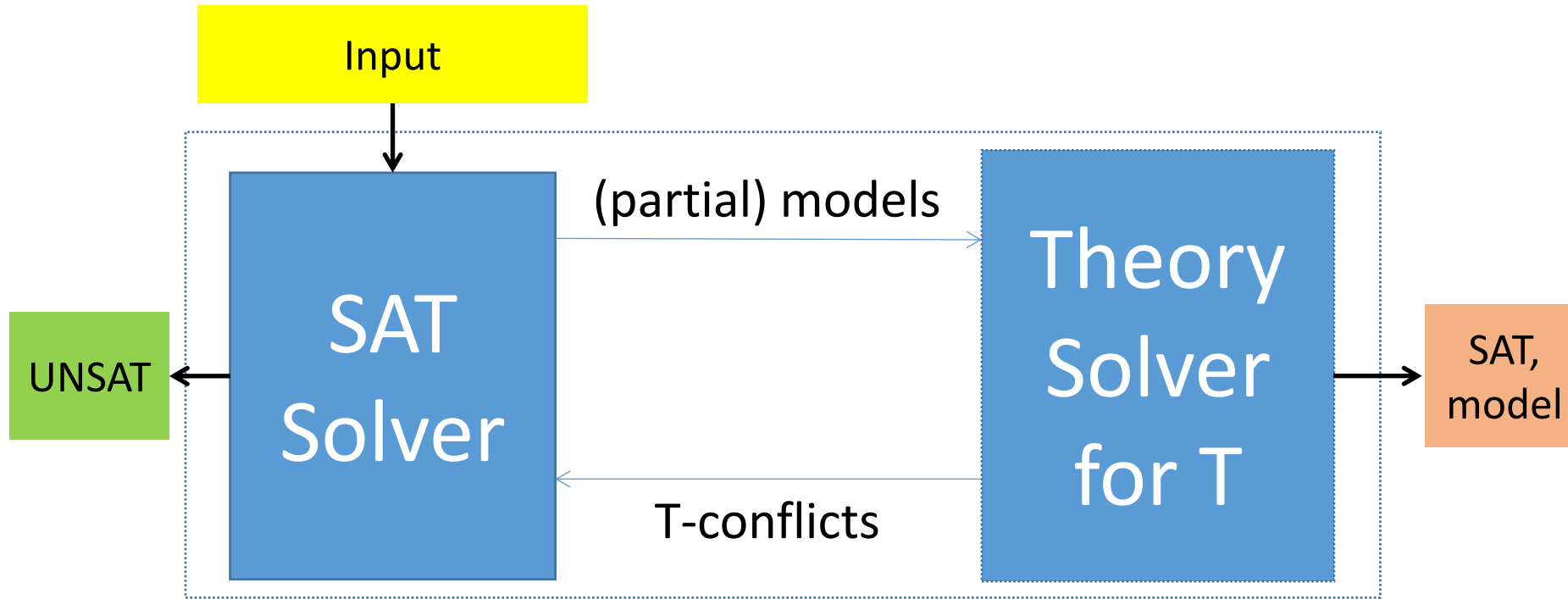
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How are Decision Procedures Implemented in SMT?



- Decision Procedures are implemented as *theory solvers*
- If M is T-unsat, find an inconsistent subset $C \subseteq M$, add conflict clause $\neg C$
- If M is T-sat, return an interpretation for variables in model of M

How are Decision Procedures Implemented in SMT?



⇒ DPLL(T) procedure [Nieuwenhuis/Oliveras/Tinelli 2007]

Design of Theory Solvers in SMT

- A DPLL(T) theory solver:
 - Should be **solution-sound**, **refutation-sound**, **terminating** for input M
 - Should produce **models** and **T-conflicts**
 - Should be designed to work *incrementally*
 - M is constantly being appended to/backtracked upon
 - Should compute useful **T-propagations**
 - Should **cooperate** with other theory solvers for combined theories
 - [Nelson/Oppen 1979]

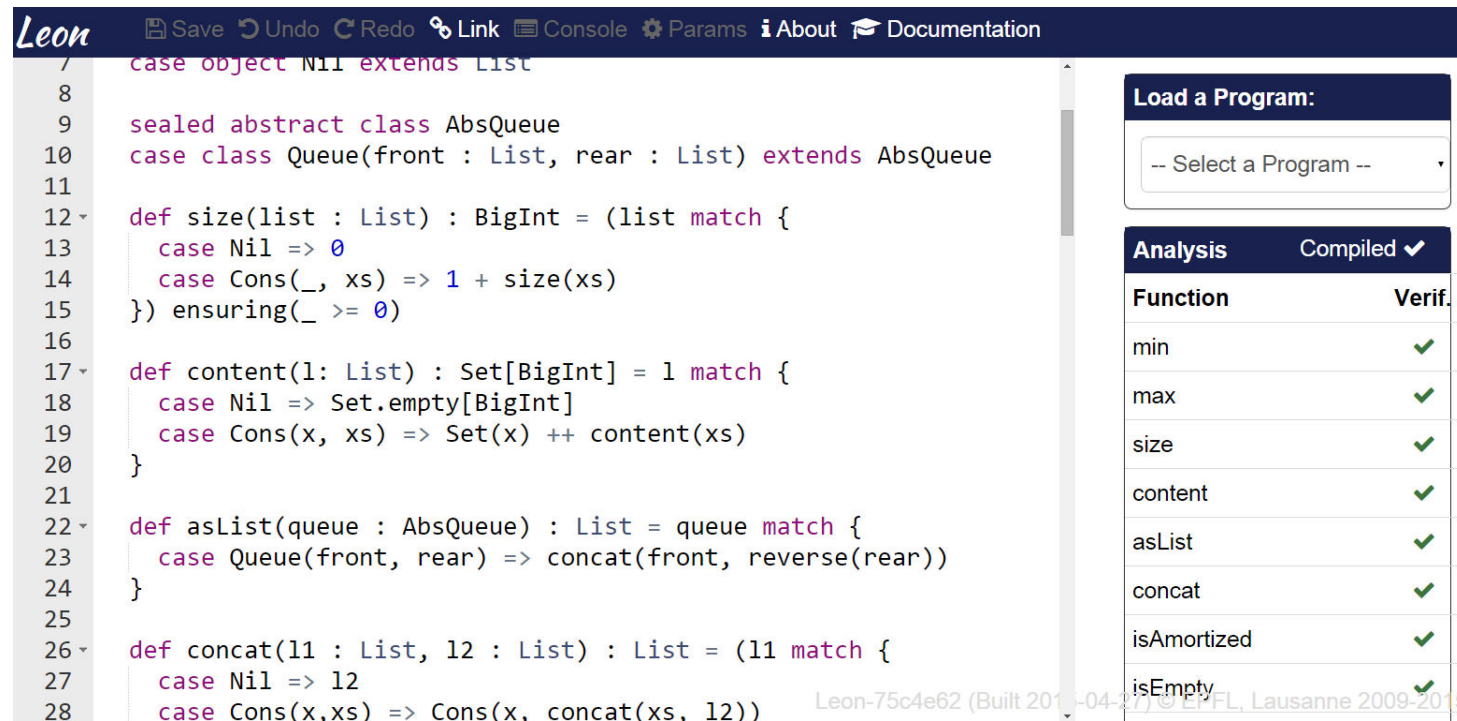
Examples of Decision Procedures in SMT

- Efficient theory solvers have been developed for:
 - Theory of Equality and Uninterpreted Functions (EUF)
 - Congruence closure algorithm [Nieuwenhuis/Oliveras 2007]
 - Theory of Linear Integer/Real Arithmetic
 - Simplex algorithm [Detertre/deMoura 2006]
 - Theory of Arrays [deMoura/Bjorner 2009]
 - Theory of Bit Vectors [Brummayer/Biere 2009]
 - Theory of Inductive Datatypes [Barrett et al 2007]
 - ⇒ *Theory of (Co)Inductive Datatypes* [Reynolds/Blanchette 2015]

Theory of (Co)Inductive Datatypes

Theory of Inductive Datatypes : Applications

- Leon verification tool developed at EPFL
 - Reasons about the correctness of simple functional programs written in Scala



The screenshot shows the Leon verification tool interface. The main window displays Scala code for a queue implementation. The code includes a `Nil` case object, an `AbsQueue` abstract class, a `Queue` class, and several functions: `size`, `content`, `asList`, and `concat`. The `size` function is annotated with `ensuring(_ >= 0)`. The `content` function returns a `Set[BigInt]`. The `asList` function converts a queue to a list. The `concat` function concatenates two lists. The right sidebar shows a 'Load a Program:' dropdown menu and a table of analysis results.

```
Leon Save Undo Redo Link Console Params About Documentation
7 case object Nil extends List
8
9 sealed abstract class AbsQueue
10 case class Queue(front : List, rear : List) extends AbsQueue
11
12 def size(list : List) : BigInt = (list match {
13   case Nil => 0
14   case Cons(_, xs) => 1 + size(xs)
15 }) ensuring(_ >= 0)
16
17 def content(l: List) : Set[BigInt] = l match {
18   case Nil => Set.empty[BigInt]
19   case Cons(x, xs) => Set(x) ++ content(xs)
20 }
21
22 def asList(queue : AbsQueue) : List = queue match {
23   case Queue(front, rear) => concat(front, reverse(rear))
24 }
25
26 def concat(l1 : List, l2 : List) : List = (l1 match {
27   case Nil => l2
28   case Cons(x,xs) => Cons(x, concat(xs, l2))
```

Load a Program:
-- Select a Program --

Function	Verif.
min	✓
max	✓
size	✓
content	✓
asList	✓
concat	✓
isAmortized	✓
isEmpty	✓

Leon-75c4e62 (Built 2015-04-30) © EPFL, Lausanne 2009-2015

- Makes heavy use of **SMT solver backend** with support for **inductive datatypes**

Theory of Inductive Datatypes

- Family of theories specified by a set of *types* with *constructors*, e.g:

$$\text{List} := \text{cons}(\text{head} : \text{Int}, \text{tail} : \text{List}) \mid \text{nil}$$

- Theory of Inductive Datatypes (DT) for Lists of Int
 - $\Sigma_{\text{DT}} : \{ \text{cons}, \text{head}, \text{tail}, \text{nil} \}$
 - Interpretations I_{DT} are such that:
 - Constructors are distinct... $\text{cons}(x,y) \neq \text{nil}$
 - Constructors are injective... if $\text{cons}(x_1, y_1) = \text{cons}(x_2, y_2)$, then $x_1 = x_2, y_1 = y_2$
 - Constructors are exhaustive... top symbol of all lists is either cons or nil
 - Selectors access subfields... $\text{head}(\text{cons}(x, y)) = x$
 - Terms do not contain themselves as subterms... $y \neq \text{cons}(x, y)$
- **My work:** decision procedure for DT in CVC4, based on [Barrett et al 2007]
 \Rightarrow *Used as a backend to Leon verification system*

What about **infinite** data structures?

- Consider the definition:

```
Stream := cons( head : Int, tail : Stream )
```

- Stream is **not well-founded**
 - ⇒ *Decision procedure for inductive datatypes does not apply*
- Instead, need decision procedure for **coinductive datatypes**
- Applications :
 - Modeling infinite processes
 - Programming languages: CoCaml [Jeannin et al 2013], Dafny [Leino 2014]
 - Proof assistants : Agda, Coq, Isabelle, ...
 - ⇒ These applications can benefit from native support for them **in SMT solvers**

Theory of (Co)Inductive Datatypes

- Devised a **unified decision procedure** for inductive/coinductive datatypes
 - Implemented in CVC4

$$\frac{t \in \mathcal{T}(E)}{E := E, t \approx t} \text{Refl} \quad \frac{t \approx u \in E}{E := E, u \approx t} \text{Sym} \quad \frac{s \approx t, t \approx u \in E}{E := E, s \approx u} \text{Trans}$$

$$\frac{\bar{t} \approx \bar{u} \in E \quad f(\bar{t}), f(\bar{u}) \in \mathcal{T}(E)}{E := E, f(\bar{t}) \approx f(\bar{u})} \text{Cong} \quad \frac{t \approx u, t \not\approx u \in E}{\perp} \text{Conflict}$$

$$\frac{C(\bar{t}) \approx C(\bar{u}) \in E}{E := E, \bar{t} \approx \bar{u}} \text{Inject} \quad \frac{C(\bar{t}) \approx D(\bar{u}) \in E \quad C \neq D}{\perp} \text{Clash}$$

$$\frac{\delta \in \mathcal{Y}_{\text{dt}} \quad \mathcal{A}[t^\delta] = \mu x. u \quad x \in \text{FV}(u)}{\perp} \text{Acyclic} \quad \frac{\delta \in \mathcal{Y}_{\text{codt}} \quad \mathcal{A}[t^\delta] =_\alpha \mathcal{A}[u^\delta]}{E := E, t \approx u} \text{Unique}$$

- For codatatypes:
 - Terms *can* contain themselves as subterms : $x = \text{cons}(z, x)$ is satisfiable
 - Terms are unique up to α -equivalence:
 - If $x = \text{cons}(z, x)$ and $y = \text{cons}(z, y)$, then $x = y$

Theory of (Co)Inductive Datatypes

	Distro		AFP		G&L		Overall	
	CVC4	Z3	CVC4	Z3	CVC4	Z3	CVC4	Z3
No (co)datatypes	221	209	775	777	52	51	1048	1037
Datatypes without Acyclic	227	–	780	–	52	–	1059	–
Full datatypes	227	213	786	791	52	51	1065	1055
Codatatypes without Unique	222	–	804	–	56	–	1082	–
Full codatatypes	223	–	804	–	59	–	1086	–
Full (co)datatypes	229	–	815	–	59	–	1103	–

- Experimental results: Implementation in CVC4 improves state of the art
 - Evaluated on proof obligations from Isabelle theorem prover

Theory Solvers for Harder Theories?

- So far: theory solvers for decision procedures
- However, in practice a theory solver **need not be complete**
 - E.g. what if background theory is **undecidable**?
- Examples of problems that use **incomplete** theory solvers:
 - Theory of Non-Linear (Integer) Arithmetic
 - ⇒ *Theory of Strings + Length constraints* [[Liang/Reynolds/Tinelli/Barrett/Deters CAV14](#)]

Theory of Strings + Length

Theory of Strings : Applications

```
char buff[15];
char pass;
cout << "Enter the password :";
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        pass = 'Y';
    }
}
if(pass == 'Y') {
    /* Grant the root permission*/
}
```

Encode

```
(set-logic QF_S)
(declare-const input String)
(declare-const buff String)
(declare-const pass0 String)
(declare-const rest String)
(declare-const pass1 String)
(assert (= (str.len buff) 15))
(assert (= (str.len pass1) 1))
(assert (or (< (str.len input) 15)
            (= input (str.++ buff pass0 rest))))
(assert (str.in.re buff
                    (re.+ (re.range "A" "Z"))))
(assert (ite (= buff "PASSWORD")
            (= pass1 "Y")
            (= pass1 pass0)))
(assert (not (= buff "PASSWORD")))
(assert (= pass1 "Y"))
```

Extract

Solve

```
tiliang@milner:~/workspace/security/benchmarks/homemade$ ~/CVC4/bin/pt-cvc4 propsalex.smt2
sat
(model
  (define-fun input () String "AAAAAAAAAAAAAAAAAY")
  (define-fun buff () String "AAAAAAAAAAAAAAAA")
  (define-fun pass0 () String "Y")
  (define-fun rest () String "")
  (define-fun pass1 () String "Y")
)
```

- Security applications frequently rely on reasoning about **string** constraints

Theory of Strings + Length

- Signature Σ_s :
 - Constants from a fixed finite alphabet $A^* = (a, ab, cbc\dots)$
 - String concatenation $_ \cdot _ : \text{String} \times \text{String} \rightarrow \text{String}$
 - Length terms $\text{len}(_) : \text{String} \rightarrow \text{Int}$
- Example input:

$\text{len}(x) > \text{len}(y) \wedge x \cdot b = y \cdot ab$

Theory of Strings + Length

- Theoretical complexity of:
 - Word equation problem is in **PSPACE**
 - ...with length constraints is **OPEN**
 - ...with extended functions, e.g. `replace`, is **UNDECIDABLE**
- Instead, focus on:
 - Solver that is efficient in practice
 - Tightly integrated into SMT solver architecture
 - Conflict-Driven Clause Learning, Propagation, Composable with other theories

Theory of Strings : Rule-Based Procedure

...

$$\text{F-Unify} \frac{F s = (w, u, u_1) \quad F t = (w, v, v_1) \quad s \approx t \in \mathcal{C}(S) \quad S \models \text{len } u \approx \text{len } v}{S := S, u \approx v}$$

$$\text{F-Split} \frac{F s = (w, u, u_1) \quad F t = (w, v, v_1) \quad s \approx t \in \mathcal{C}(S) \quad S \models \text{len } u \neq \text{len } v \quad u \notin \mathcal{V}(v_1) \quad v \notin \mathcal{V}(u_1)}{S := S, u \approx \text{con}(v, z) \quad || \quad S := S, v \approx \text{con}(u, z)}$$

$$\text{F-Loop} \frac{F s = (w, x, u_1) \quad F t = (w, v, v_1, x, v_2) \quad s \approx t \in \mathcal{C}(S) \quad x \notin \mathcal{V}((v, v_1))}{S := S, x \approx \text{con}(z_2, z), \text{con}(v, v_1) \approx \text{con}(z_2, z_1), \text{con}(u_1) \approx \text{con}(z_1, z_2, v_2) \quad R := R, z \text{ in star}(\text{set con}(z_1, z_2)) \quad C := C, t}$$

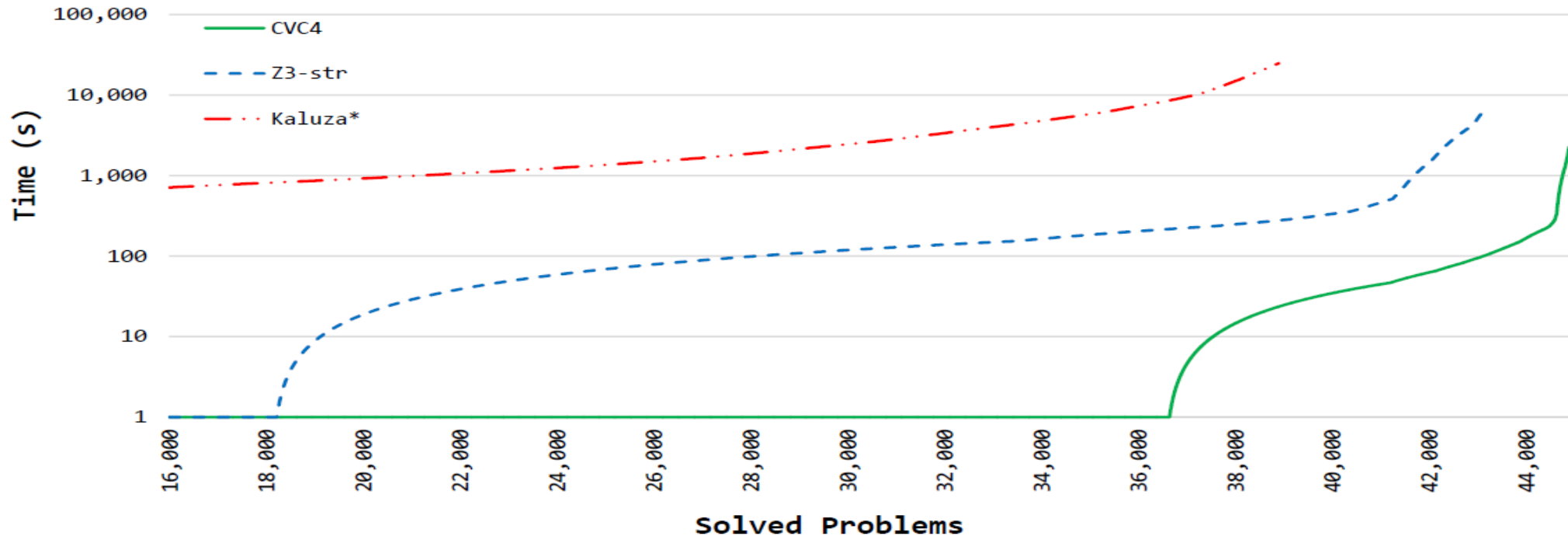
...

- Existing approaches rely on reduction to bitvectors, e.g. HAMPI [Kiezun 2009]
- Instead, we use an **algebraic** rule-based procedure for strings, which:
 - Infers equalities over strings based on length constraints
 - Models interaction of string + arithmetic solvers
 - Recognizes conflicts due to cardinality of alphabet

Theory of Strings : Theoretical Results

- For strings + length:
 - Procedure is:
 - **Refutation sound**, even for strings of unbounded length
 - **Solution sound**
 - (A version of) procedure is:
 - **Solution complete**
 - When problem is “SAT”, it will eventually find a model (finite model finding)
 - When input is in acyclic form (variables only on 1 side of equalities),
 - **Refutation complete**
 - When problem is “UNSAT”, it will derive a refutation

Theory of Strings : Experimental Results



- Tested 50,000 VCs in web security applications (Kudzu)
- Implementation in CVC4 significantly improved state-of-the-art
 - In terms of **precision**, **performance**, and **accuracy**

Extending the Theory of Strings

- Theory of strings can be **extended** with support for:
 - Regular expressions
 - E.g. $x \in (a \cup (bb)^*)^*$
 - Decision procedure for regular memberships + length [\[submitted, FroCos15\]](#)
 - Regular languages
 - E.g. $x \in (y \cdot b)^*$
 - Extended functions
 - E.g. `substr`, `contains`, `replace`, `prefixOf`, `suffixOf`, `str.indexOf`, `str.to.int`, `int.to.str`, `strcmp`
 - Occur frequently in practice
 - When signature includes these, problem is generally undecidable

What about arbitrary quantified formulas?

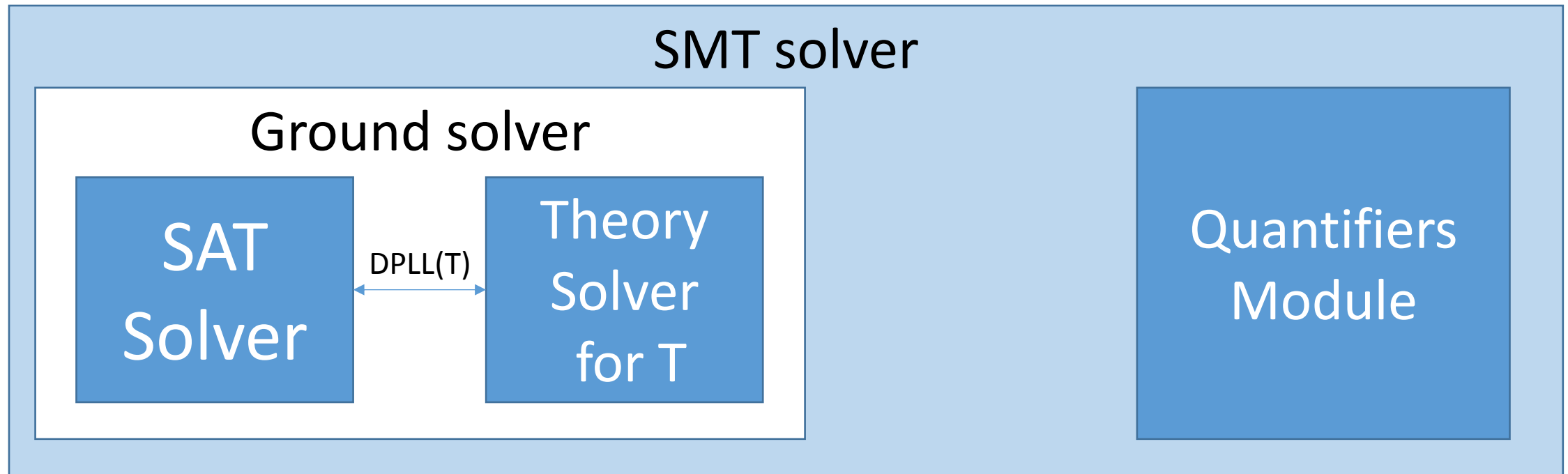
- What if constraints **do not fit** an existing theory/decision procedure?
 - Frame axioms in software verification
 - Universal safety properties
 - Axiomatization of unsupported theories
 - ...
- Want SMT solver to handle arbitrary first-order **quantified formulas**
 - E.g. $\forall x. f(x) > 0$, $\forall x. \text{select}(A, x) = 2 * x$

Approaches for Quantified Formulas in SMT

- **Heuristic** approaches
 - Incomplete, focus on finding unsatisfiable
 - Example:
 - E-matching [Detlefs et al 2003, Ge et al 2007, de Moura/Bjorner 2007]
 - **Complete** approaches
 - Target particular fragments of FOL
 - Examples:
 - Local theory extensions [Sofronie-Stokkermans 2005]
 - Array fragments [Bradley et al 2006, Alberti et al 2014]
 - Complete instantiation [Ge/de Moura 2009]
 - Finite model finding [[Reynolds et al 2013](#)]
- } Focus of next part of the talk

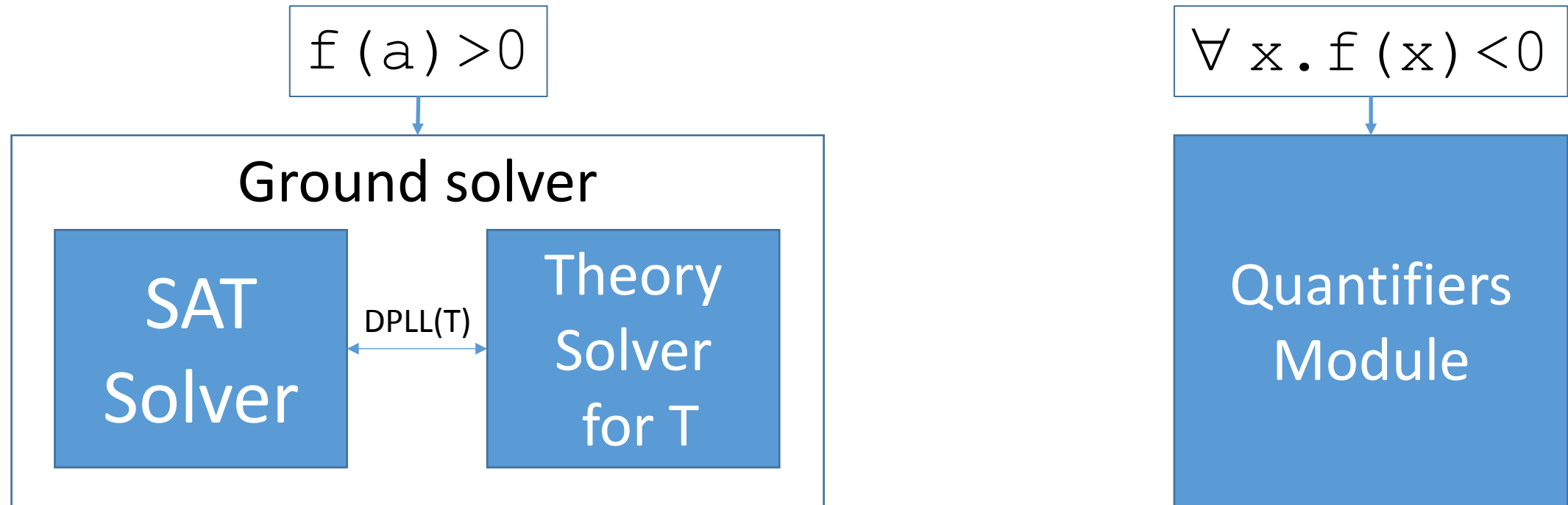
Finite Model Finding for Quantified Formulas in SMT

SMT Solver + Quantified Formulas



- SMT solvers support for (first-order) **quantified formulas** \forall

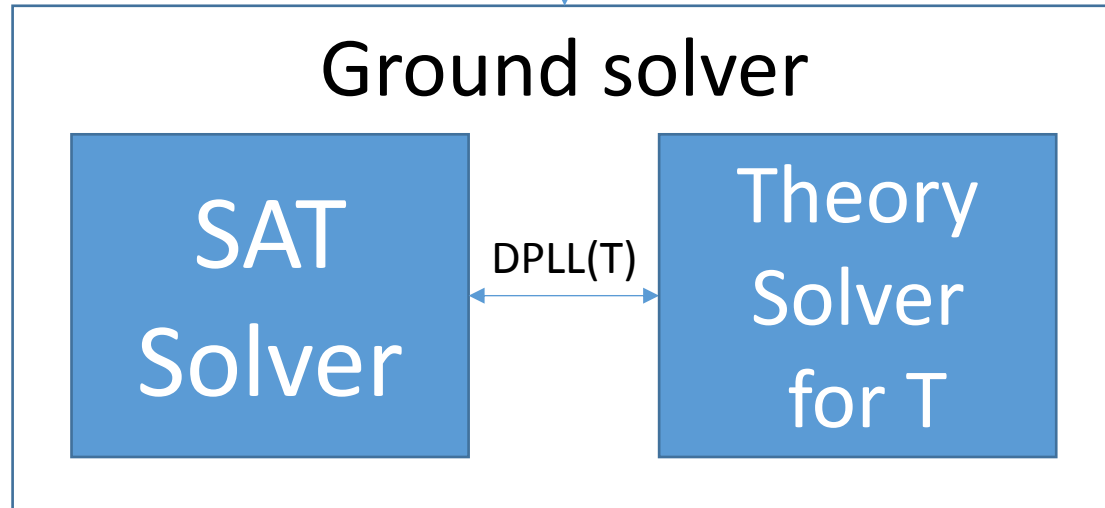
SMT Solver + Quantified Formulas



- For input $f(a) > 0 \wedge \forall x. f(x) < 0$
 - **Ground solver** maintains a set of ground (variable-free) constraints : $f(a) > 0$
 - **Quantifiers Module** maintains a set of axioms : $\forall x. f(x) < 0$

SMT Solver + Quantified Formulas

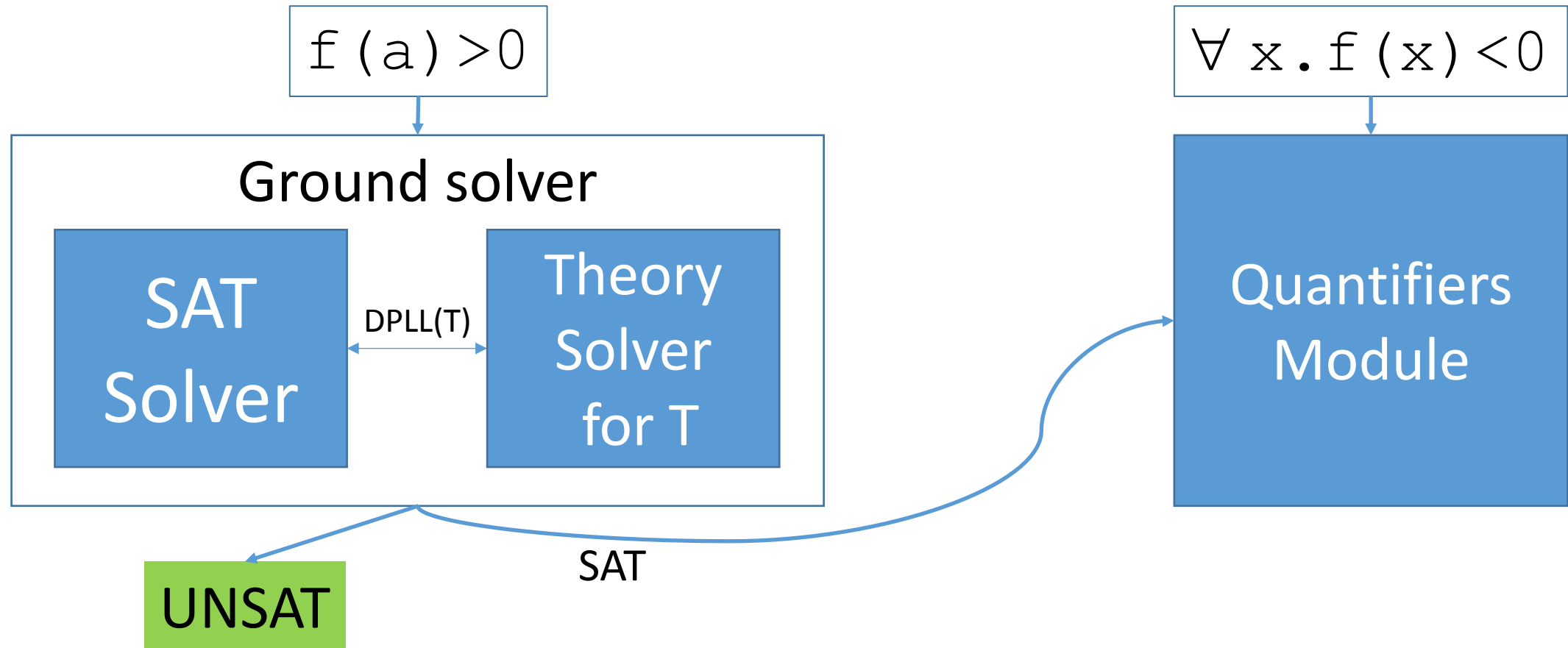
$$f(a) > 0$$



$$\forall x. f(x) < 0$$

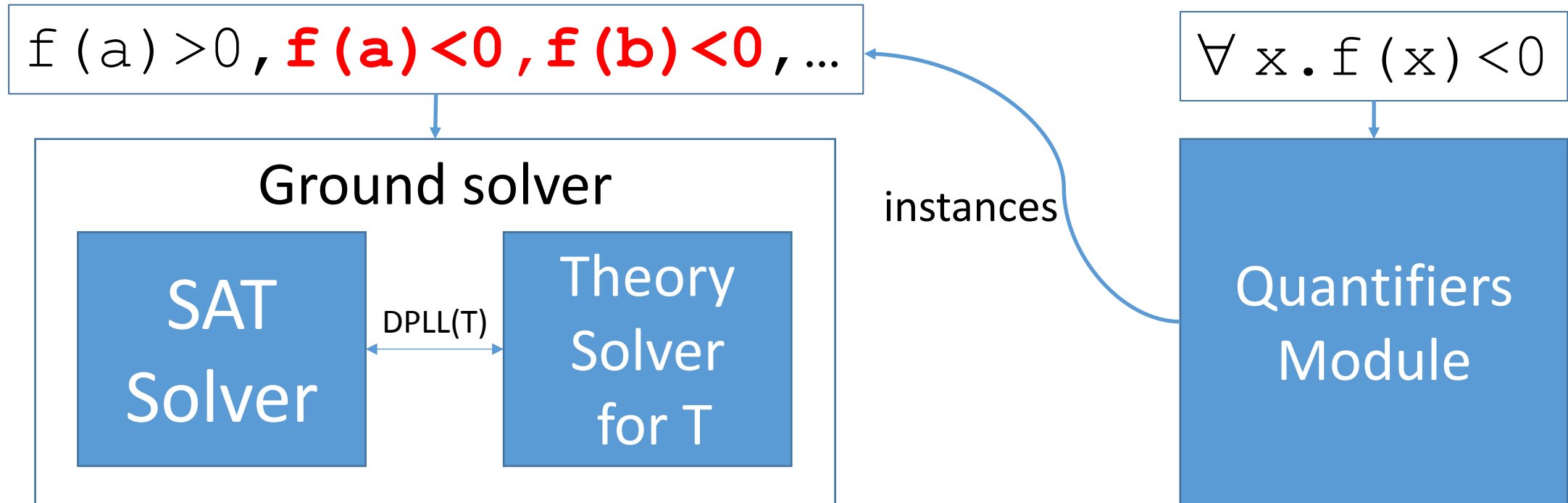


SMT Solver + Quantified Formulas



- Ground solver **checks T-satisfiability** of current set of constraints

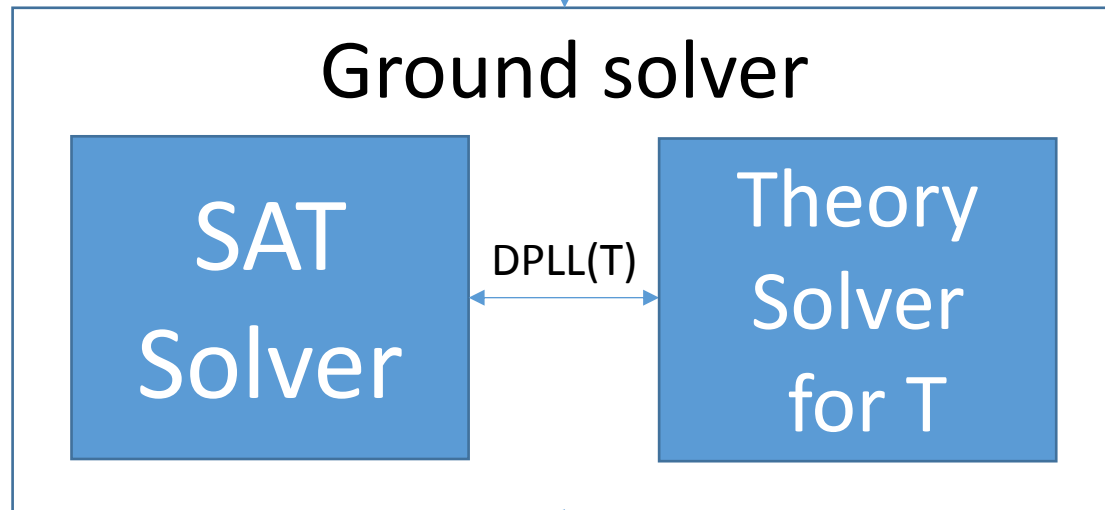
SMT Solver + Quantified Formulas



- Quantifiers Module adds **instances** of axioms
 - Goal : add instances until ground solver can answer “unsat”

SMT Solver + Quantified Formulas

$f(a) > 0, f(a) < 0, f(b) < 0, \dots$



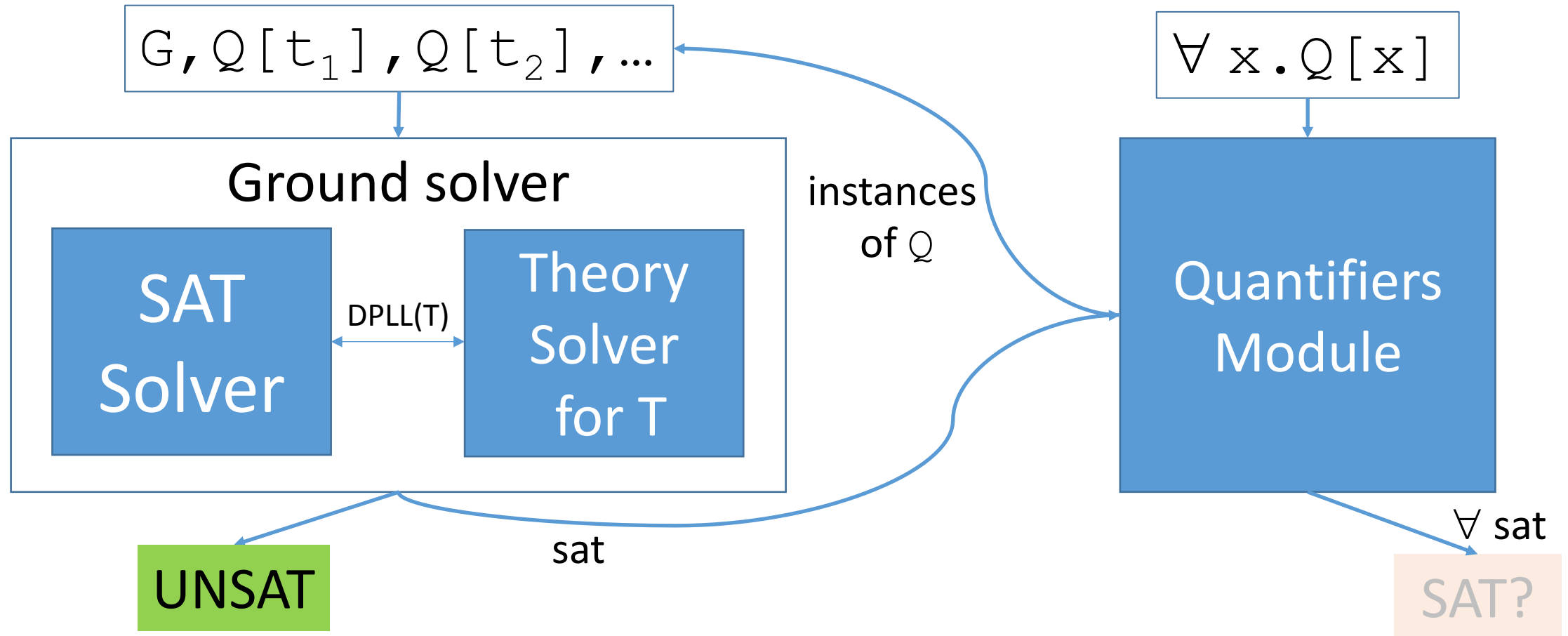
UNSAT

• Since $f(a) > 0$ and $f(a) < 0$

$\forall x. f(x) < 0$

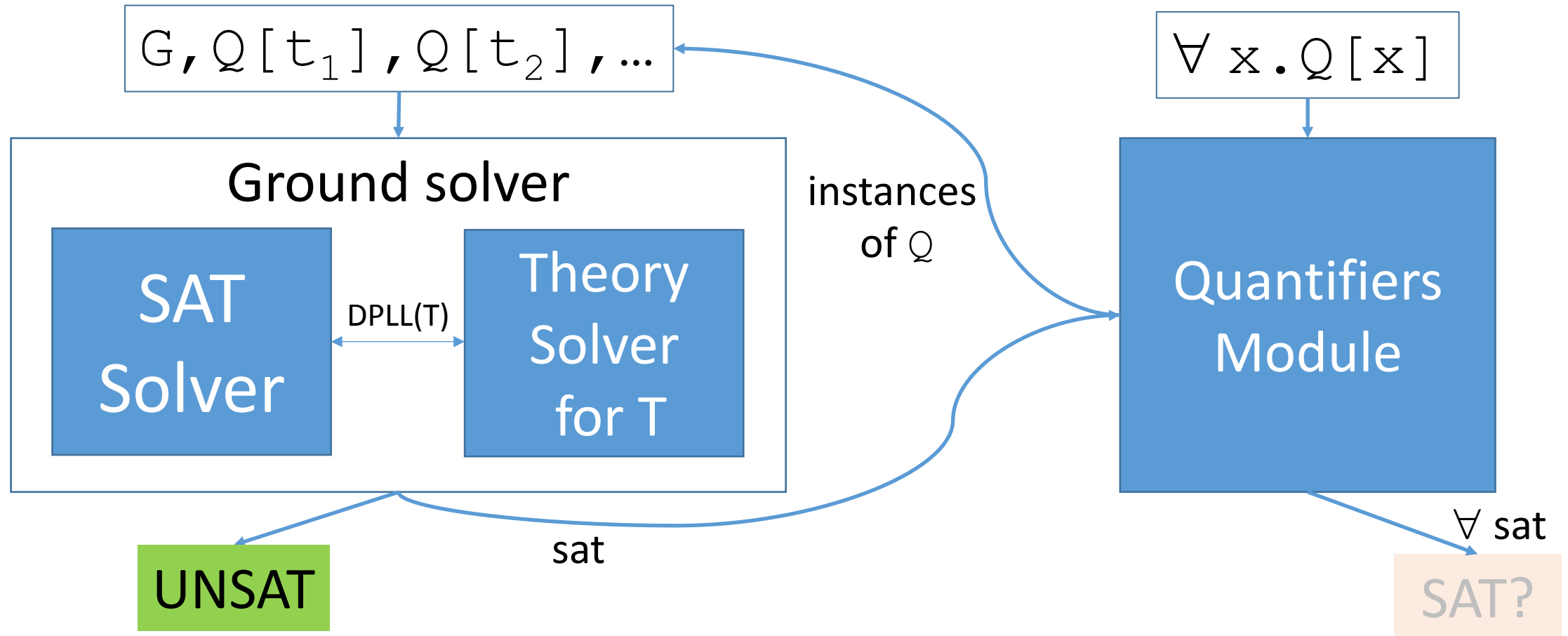


How SMT Solvers Handle Quantified Formulas



- Generally, a **sound but incomplete** procedure
 - Difficult to answer SAT (when have we added enough instances of $Q[x]$?)

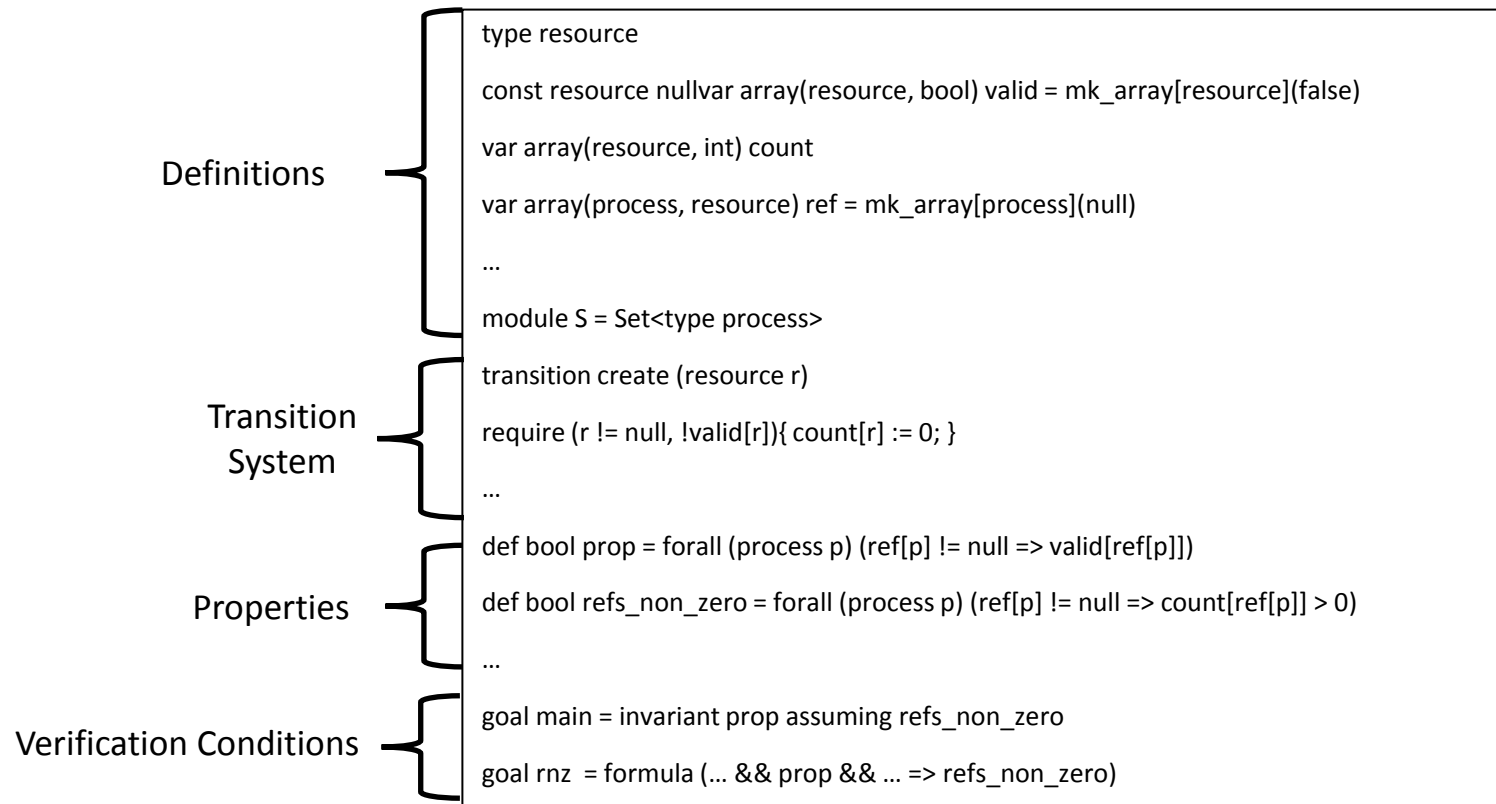
How SMT Solvers Handle Quantified Formulas



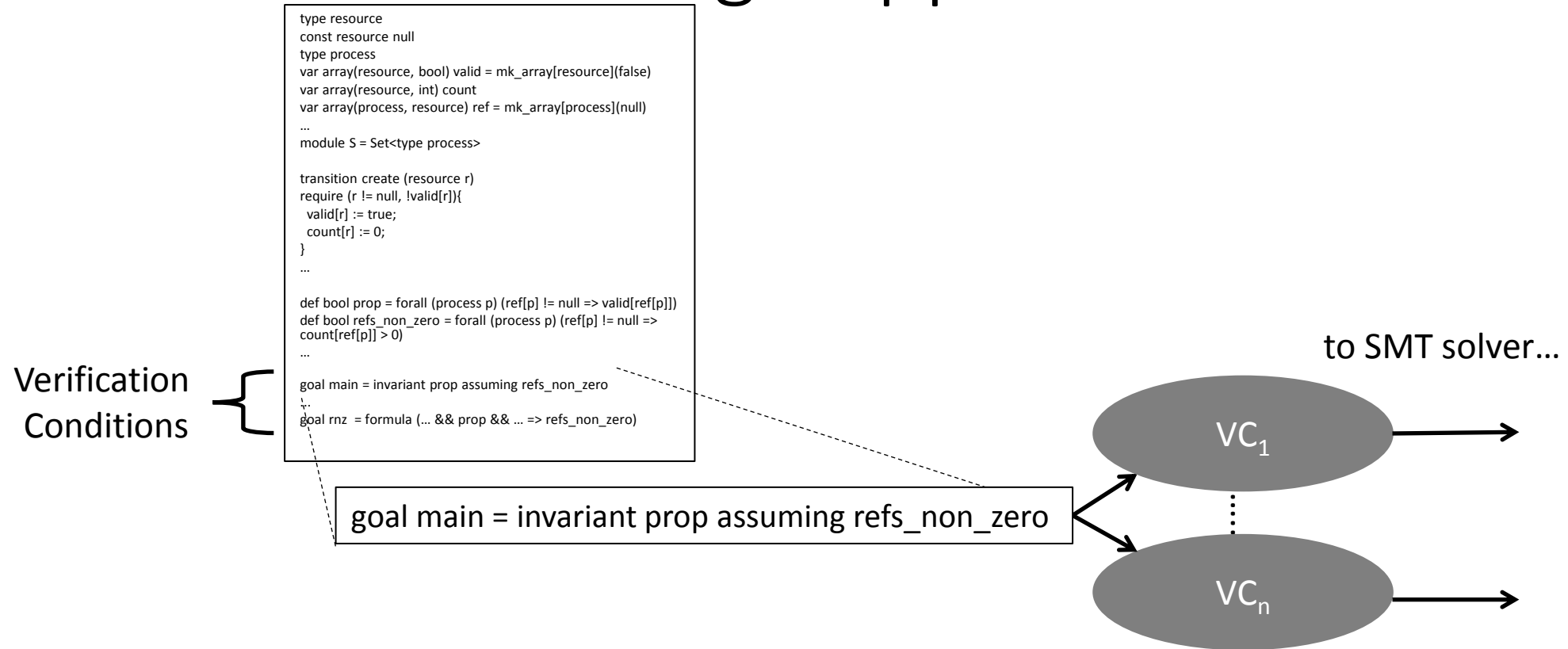
\Rightarrow Lack of ability to answer SAT is **major weakness**

Finite Model Finding : Application

- Deductive Verification Framework [Goel et al 2012] used at Intel Corporation for:
 - Architecture/Security Validation for Hardware Systems

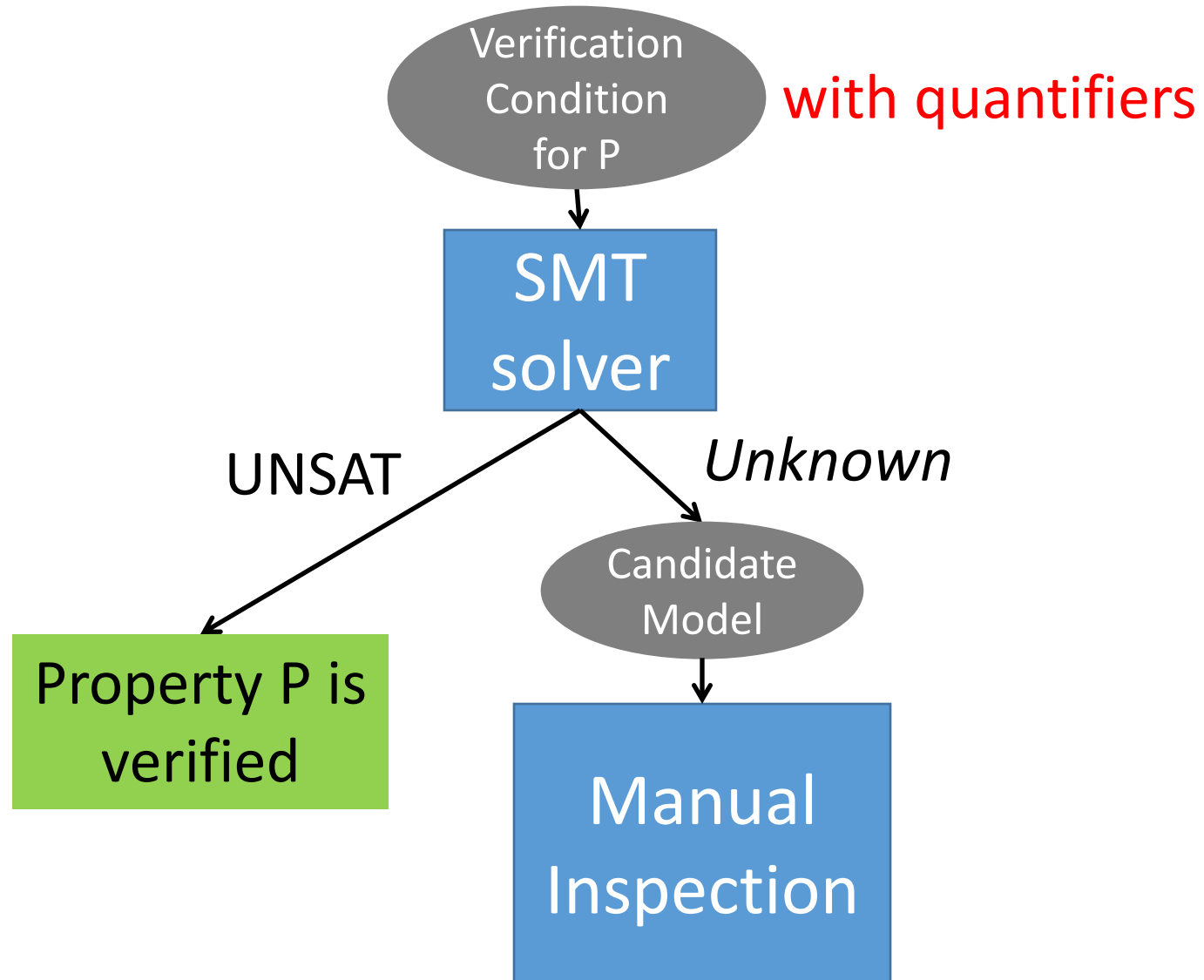


Finite Model Finding : Application

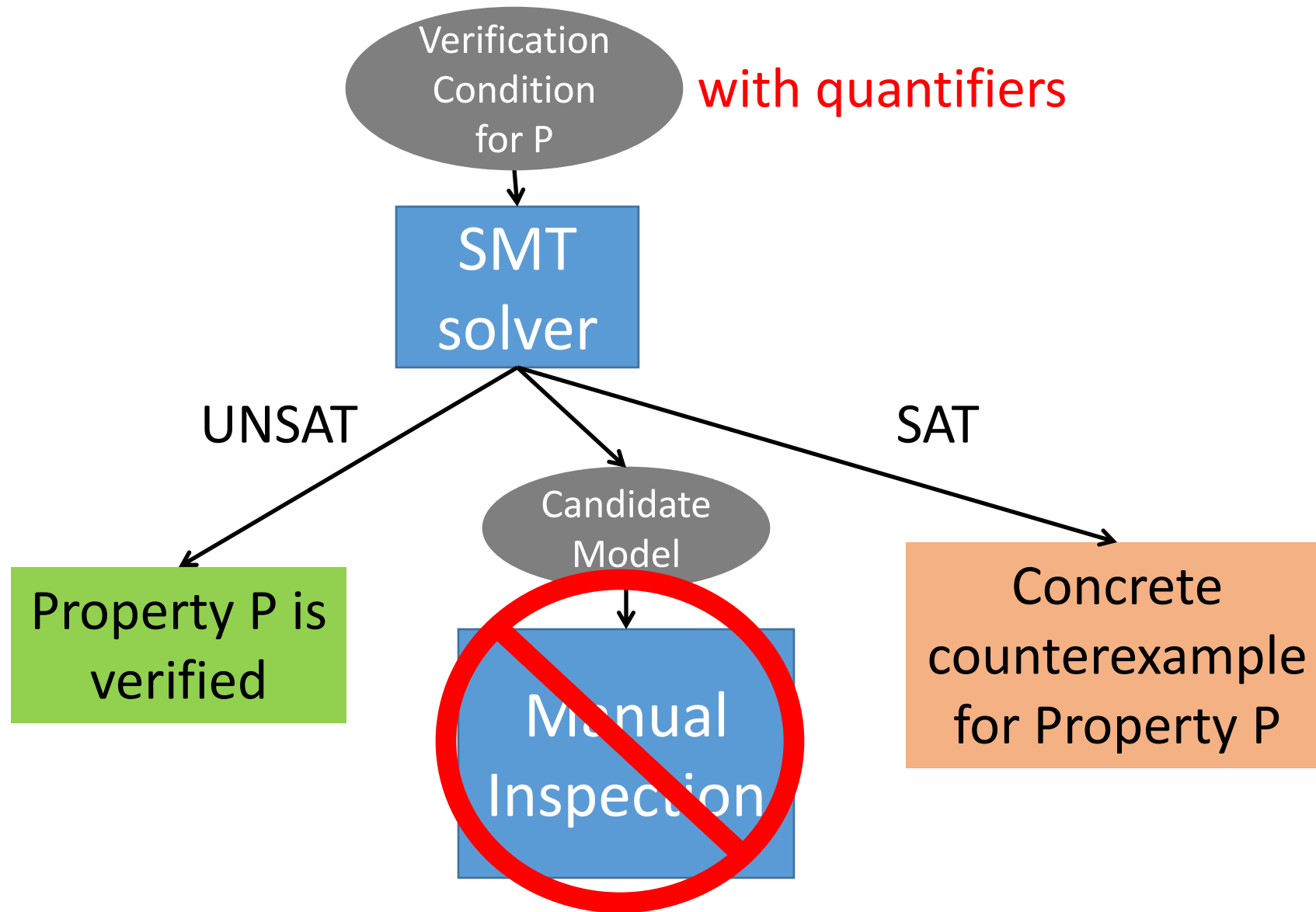


- Verification conditions translated into (multiple) SMT queries, requiring:
 - Theories (arithmetic, bit vectors, datatypes, ...)
 - **Quantified formulas** for stating universal properties over:
 - Memory addresses, resources, processes, ...

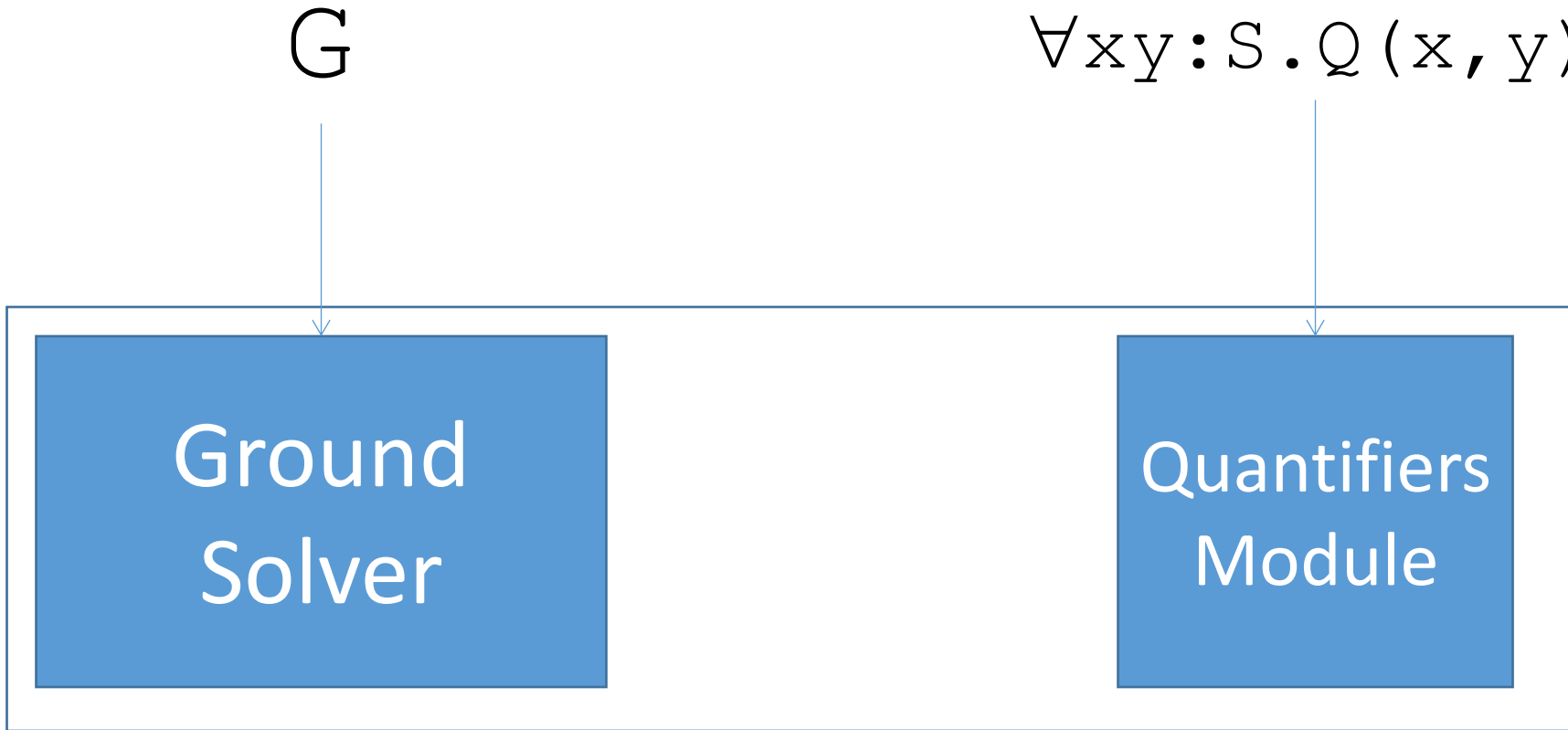
Why are Models Important?



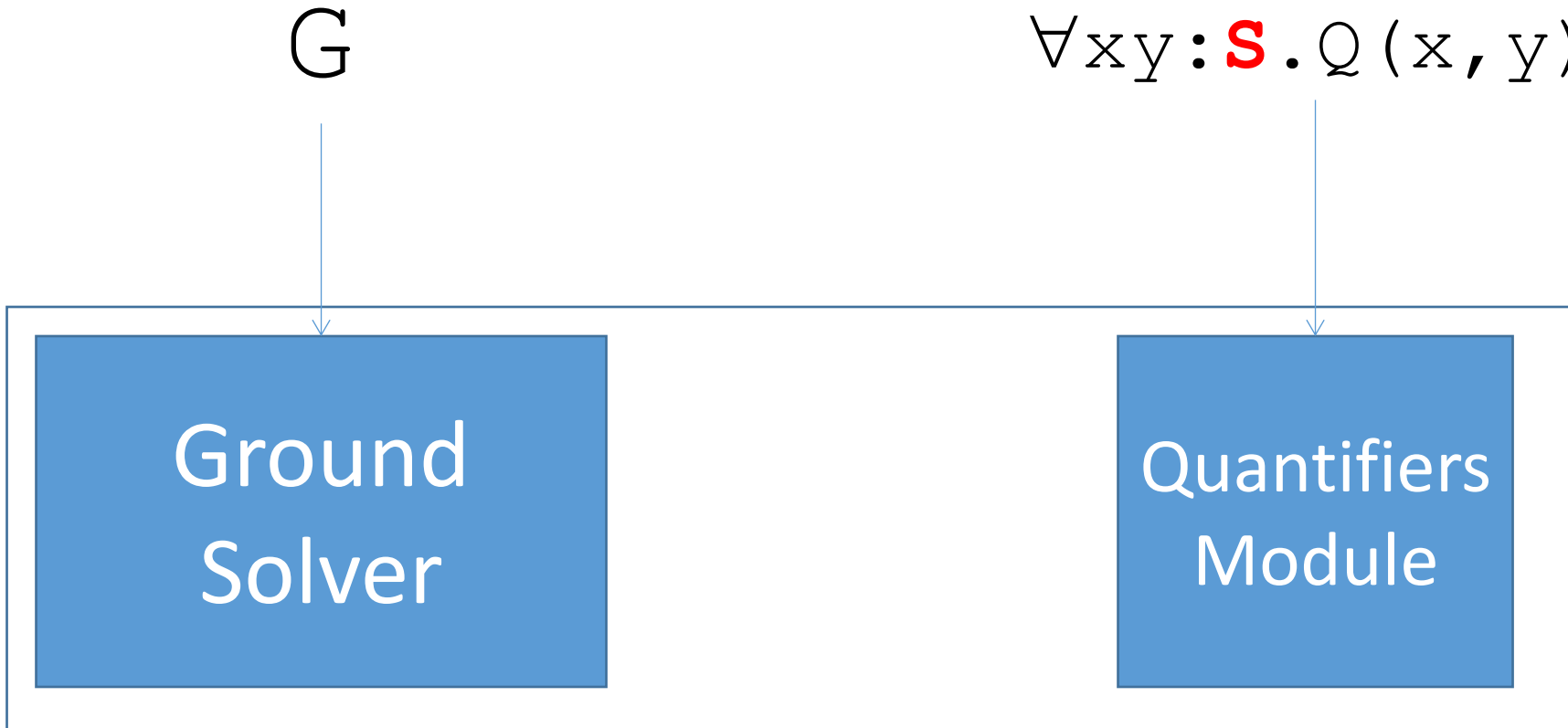
Why are Models Important?



Finite Model Finding in SMT

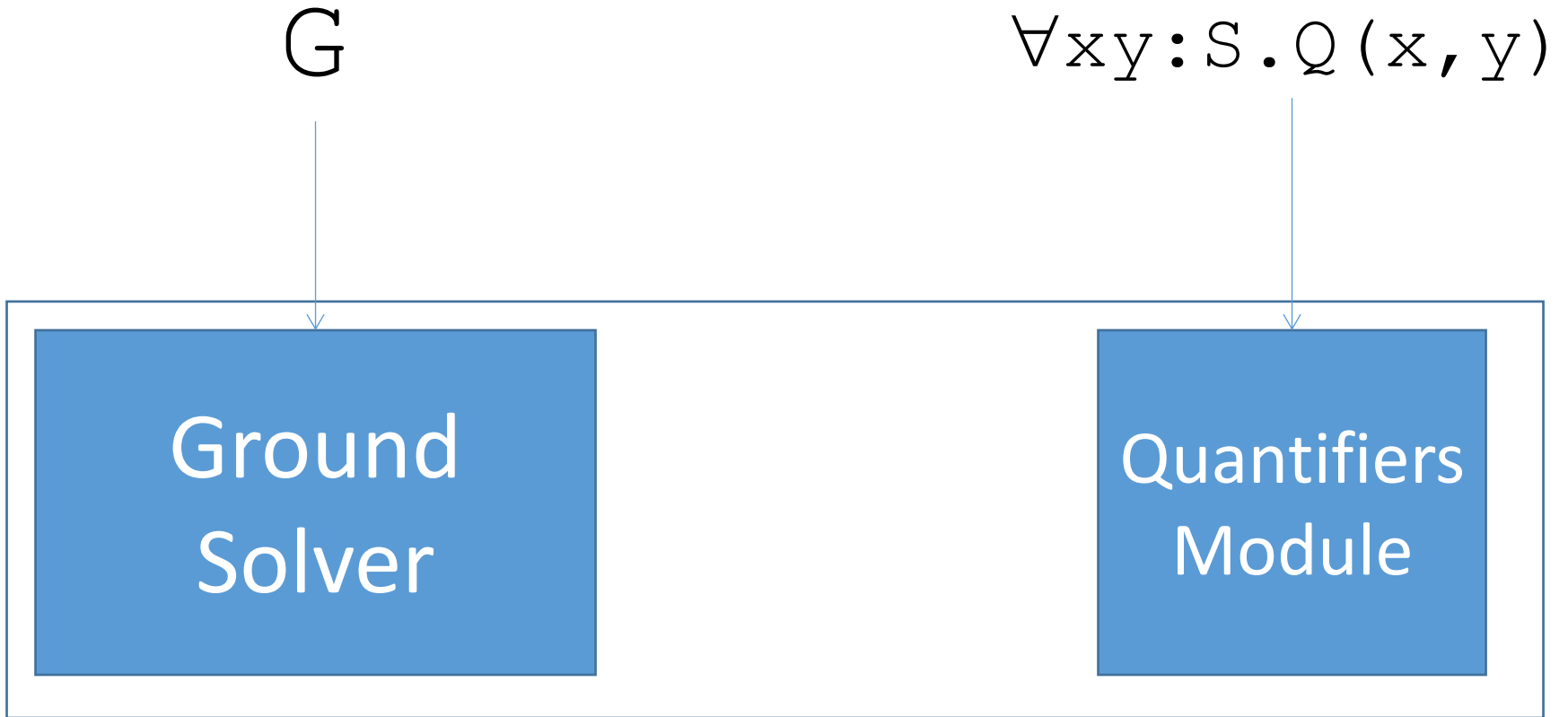


Finite Model Finding in SMT



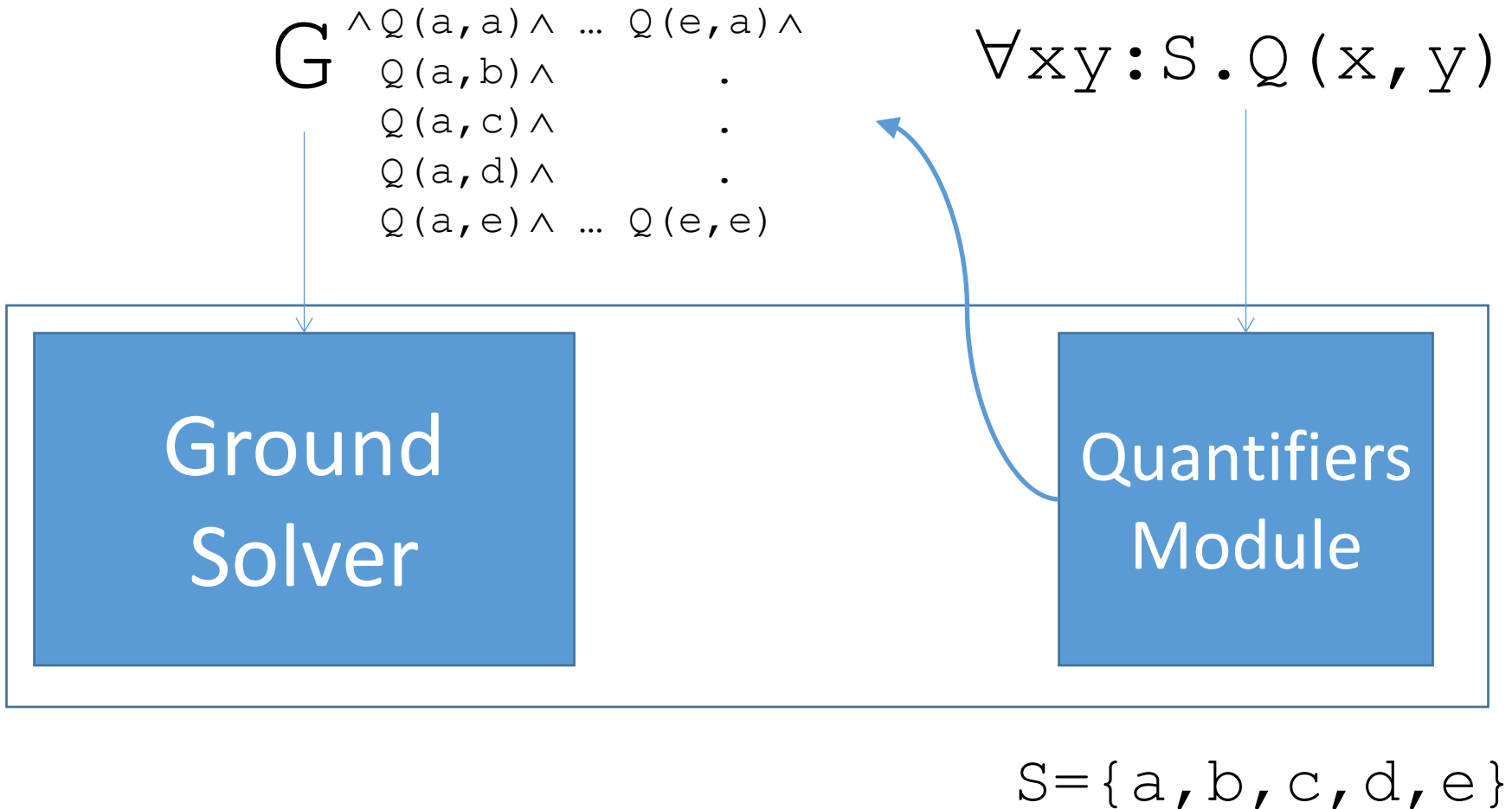
\Rightarrow If \mathbf{S} has finite interpretation,
• use finite model finding

Finite Model Finding in SMT



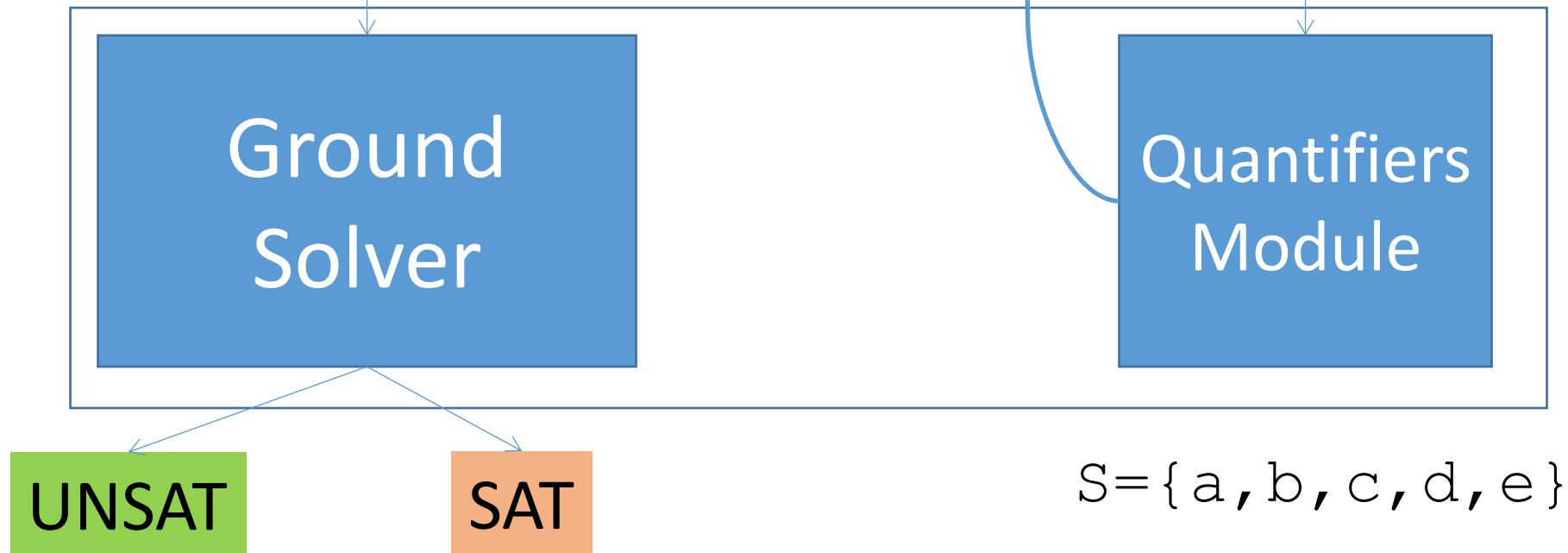
$S = \{a, b, c, d, e\}$

Finite Model Finding in SMT



- Reduction of quantified formulas to ground formulas

Finite Model Finding in SMT

$$G \wedge Q(a, a) \wedge \dots \wedge Q(e, a) \wedge$$
$$Q(a, b) \wedge \dots \wedge$$
$$Q(a, c) \wedge \dots \wedge$$
$$Q(a, d) \wedge \dots \wedge$$
$$Q(a, e) \wedge \dots \wedge Q(e, e)$$
$$\forall x, y : S. Q(x, y)$$


\Rightarrow Ability to answer SAT, assuming decision procedure for $G \wedge Q(a, a) \wedge \dots$

Finite Model Finding in SMT

$G \wedge Q(a, a) \wedge \dots \wedge Q(e, a) \wedge$
 $Q(a, b) \wedge \dots$
 $Q(a, c) \wedge \dots$
 $Q(a, d) \wedge \dots$
 $Q(a, e) \wedge \dots \wedge Q(e, e)$

$\forall x, y : S. Q(x, y)$

• *Can be very large*



UNSAT

SAT

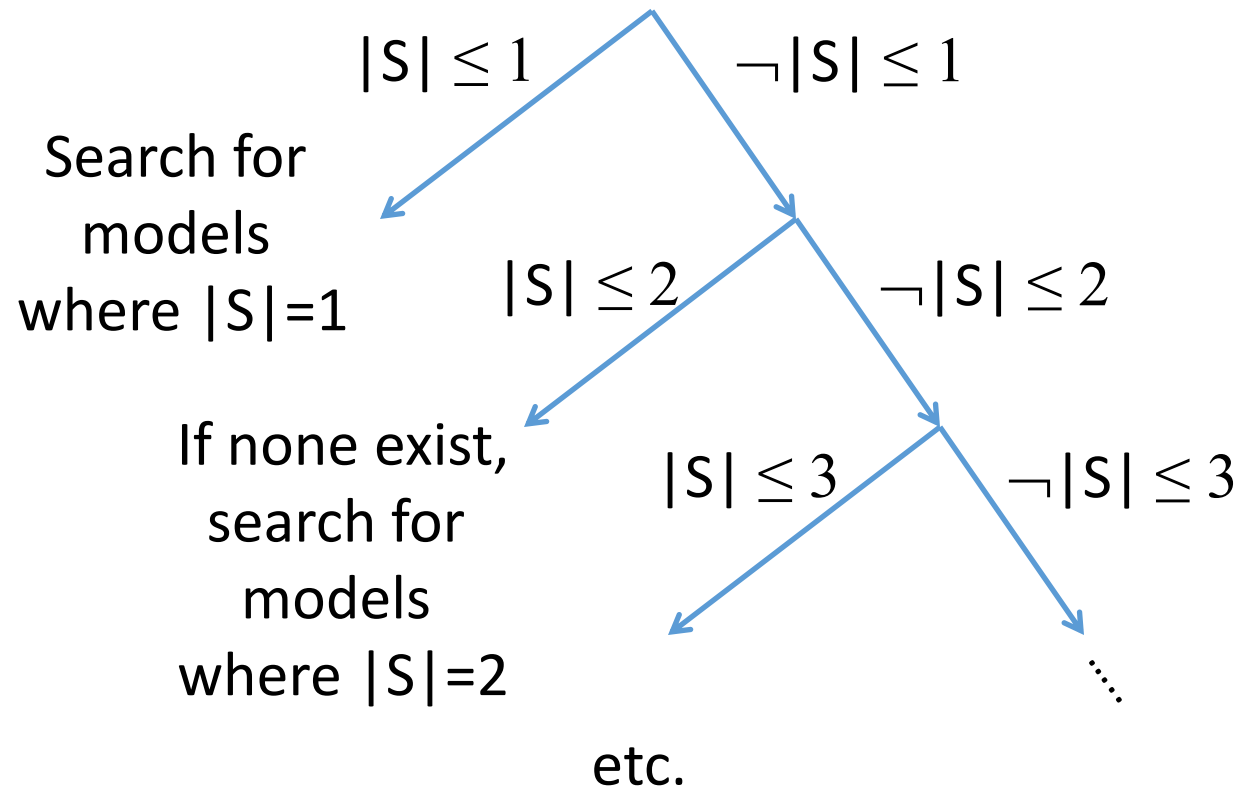
$S = \{a, b, c, d, e\}$

Finite Model Finding in SMT

- Address large # instantiations by:
 1. Minimizing model sizes [\[Reynolds et al CAV13\]](#)
 - Find interpretation that minimizes the #elements in S
 2. Only add instantiations that refine model [\[Reynolds et al CADE13\]](#)
 - Model-based quantifier instantiation [Ge/deMoura CAV 2009]

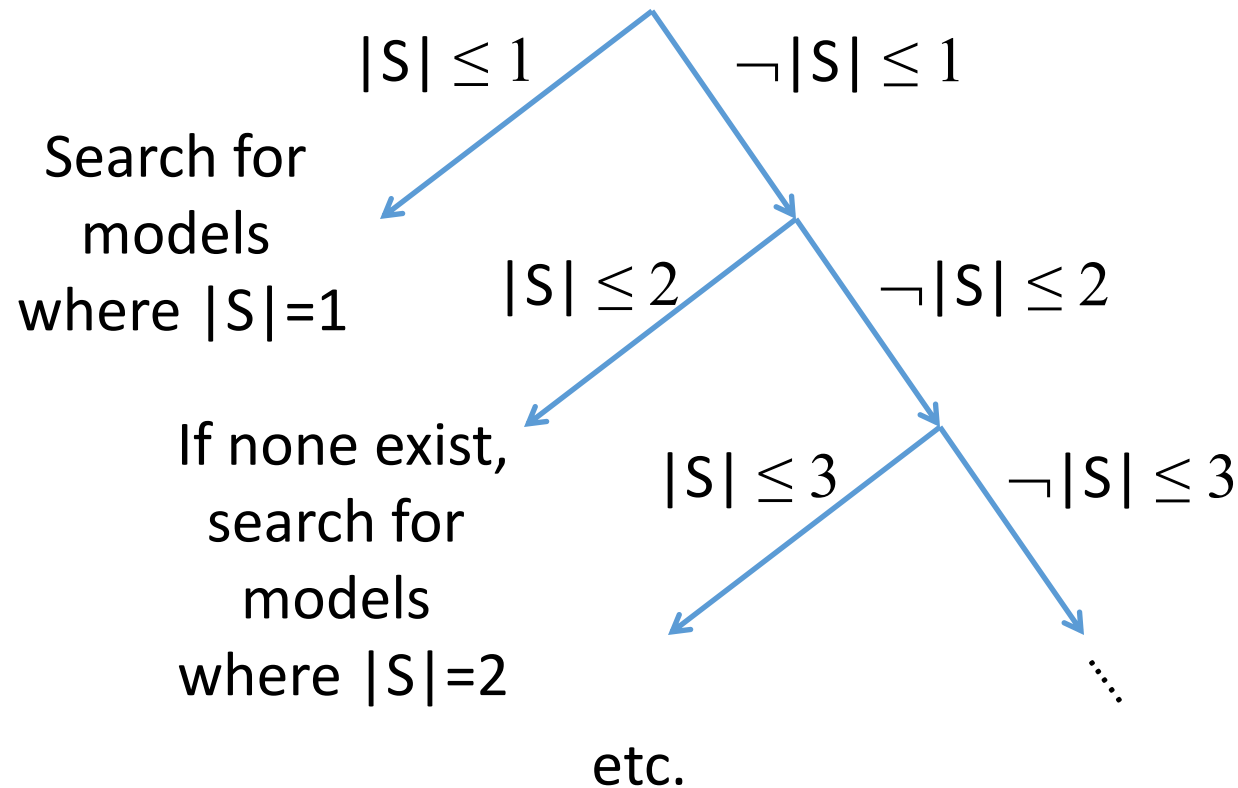
Finite Model Finding : Minimizing Model Sizes

- Minimize model sizes using a **theory solver for cardinality constraints**



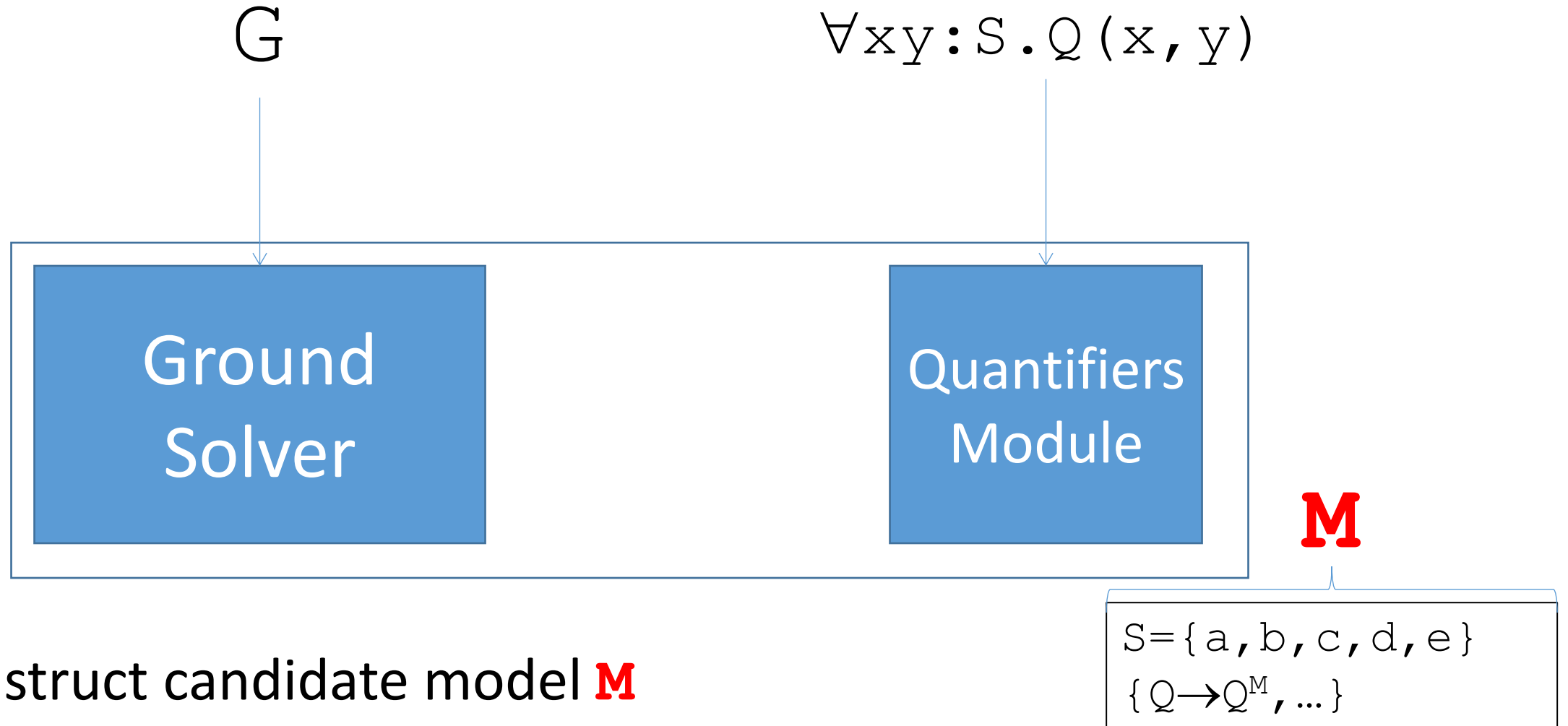
Finite Model Finding : Minimizing Model Sizes

- Minimize model sizes using a theory solver for cardinality constraints



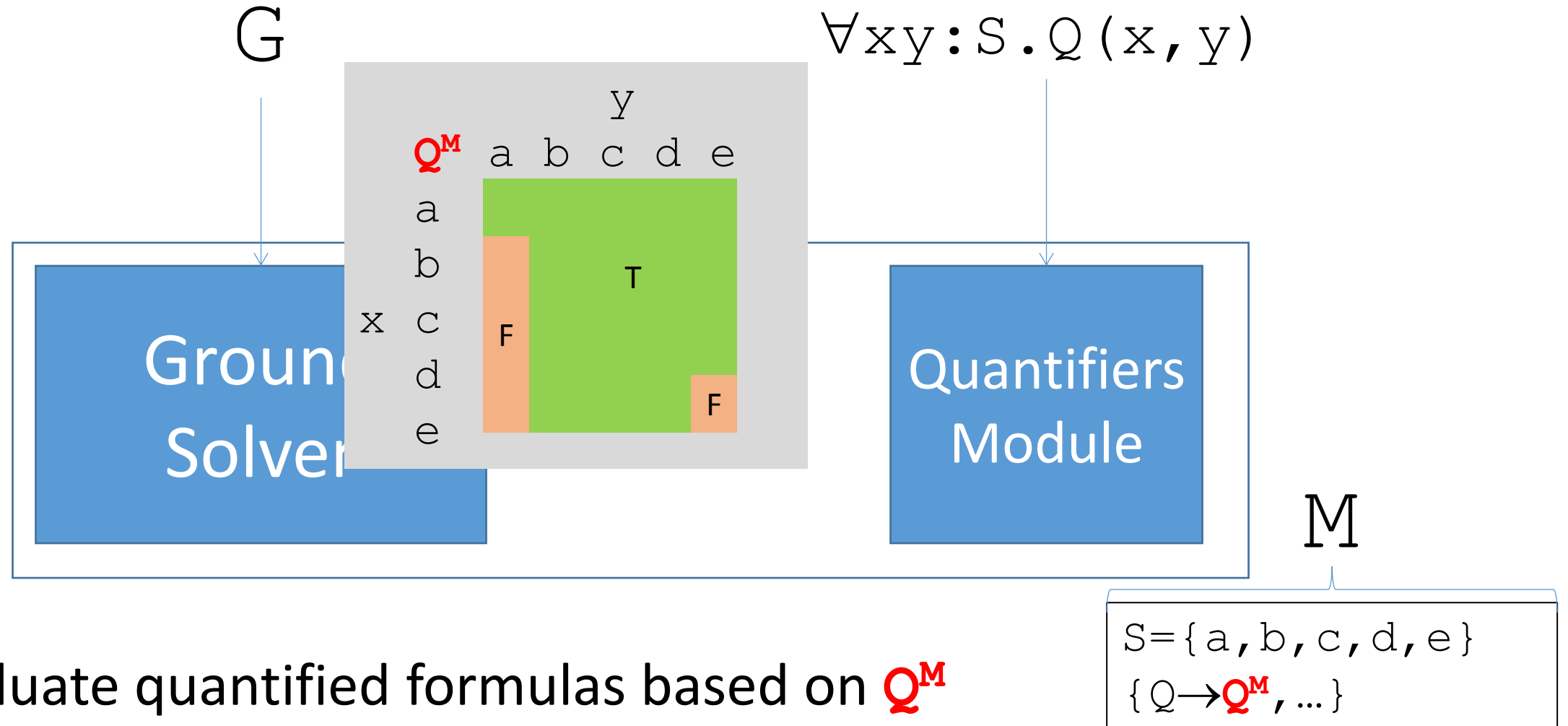
\Rightarrow If model exists where $|S| \leq 3$, only need $3*3=9$ instances instead of $5*5=25$ instances

Finite Model Finding : Model-Based Instantiation



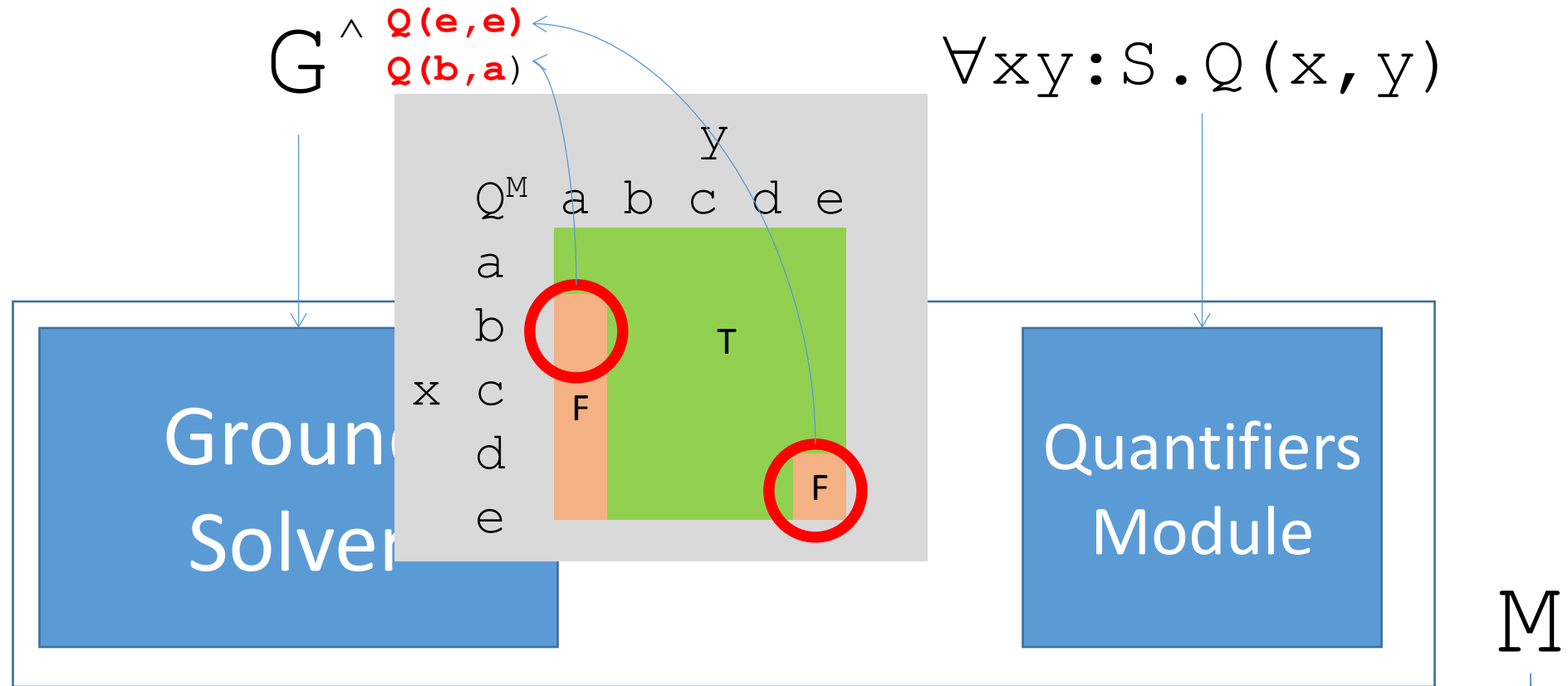
- Construct candidate model **M**

Finite Model Finding : Model-Based Instantiation



- Evaluate quantified formulas based on Q^M

Finite Model Finding : Model-Based Instantiation



- Only add instances that **evaluate to F** in Q^M
 \Rightarrow Significantly increased scalability

$S = \{a, b, c, d, e\}$
 $\{Q \rightarrow Q^M, \dots\}$

Results : Hardware Verification at Intel

SAT	german	refcount	agree	apg	bmk	Total	Time
#	45	6	42	19	37	149	
z3	45	1	0	0	0	46	8.1
cvc4	2	0	0	0	0	2	0.0
cvc4+f	45	6	42	19	37	149	409.8

UNSAT	german	refcount	agree	apg	bmk	Total	Time
#	145	40	488	304	244	1221	
z3	145	40	488	304	244	1221	31.0
cvc4	145	40	484	304	244	1217	21.3
cvc4+f	145	40	488	302	244	1219	1185.0

cvc4 :

- f : finite model finding

- Benchmarks taken from DVF tool at Intel
- Improved state of the art for **SAT** for SMT problems with \forall
- Can be competitive for **UNSAT** as well

Results : CASC Competition

First-order Non-theorems	<u>iProver</u> 1.0-SAT	<u>Paradox</u> 3.0	<u>CVC4</u> 1.2-SAT	<u>E</u> 1.8	<u>Nitrox</u> 2013	<u>Vampire</u> 3.0-SAT	<u>E-KRHyp</u> 1.4	<u>iProver-E</u> 0.85
Solved / ₁₅₀	122/ ₁₅₀	99/ ₁₅₀	96/ ₁₅₀	79/ ₁₅₀	79/ ₁₅₀	78/ ₁₅₀	67/ ₁₅₀	37/ ₁₅₀
Av. CPU Time	52.47	2.28	25.94	20.94	29.70	15.89	7.57	30.77
Solutions	122/ ₁₅₀	99/ ₁₅₀	96/ ₁₅₀	79/ ₁₅₀	79/ ₁₅₀	78/ ₁₅₀	67/ ₁₅₀	0/ ₁₅₀
μEfficiency	165	549	204	396	36	395	292	92
SOTAC	0.28	0.23	0.19	0.22	0.24	0.20	0.19	0.15
New Solved	1/ ₄	1/ ₄	1/ ₄	1/ ₄	1/ ₄	1/ ₄	0/ ₄	0/ ₄

- Competitive with existing approaches for model finding in ATP community
- CVC4 placed 3rd in non-theorems division of CASC 24
 - Is competitive with state-of-the-art ATP systems

Ongoing work/applications

- SMT solvers with support for \forall are doing increasingly **complex tasks**:
 - As an efficient *first order theorem prover*
 - [Reynolds/Tinelli/de Moura FMCAD 2014]
 - As an *inductive reasoner for program verification*
 - [Reynolds/Kuncak VMCAI 2015]
 - As a tool for *syntax-guided software synthesis*
 - [Reynolds/Deters/Kuncak/Tinelli/Barrett CAV 2015]
 - In development: As a *program analyzer*
 - Idea: built-in support for (recursive) function definitions in SMT

```
(define-fun-rec len (x List) Int (ite (is-cons x) (1 + (len (tail x))) 0))
```

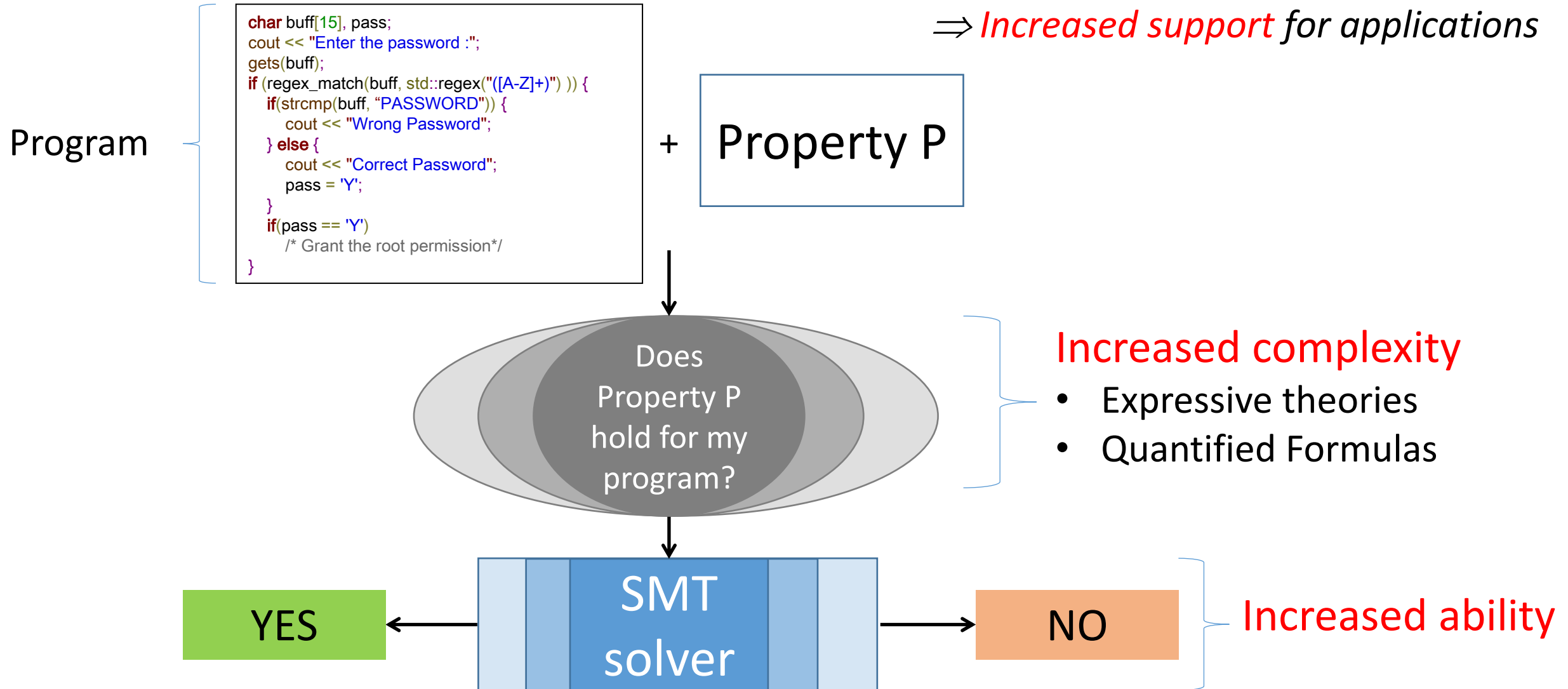
↓

```
 $\forall_{\text{len}} \mathbf{x}. \text{len}(\mathbf{x}) = (\text{ite } (\text{is-cons } \mathbf{x}) \ (1 + (\text{len } (\text{tail } \mathbf{x}))) \ 0)$ 
```


Conclusions

- Satisfiability Modulo Theories (**SMT**) is
 - **Mature** technology, both in theory and practice
 - ...but is **still evolving**:
 - Improved approaches for (combinations) of theories
 - Solvers for new theories:
 - Floating Points, Sets, *(Co)datatypes*, *Extended Strings + Length*, Regular Languages
 - ...
 - Specialized approaches for first-order quantified formulas

Conclusions



Thanks for your Attention!

- **Collaborators:**

- Cesare Tinelli, Clark Barrett, Morgan Deters, Tim King, Liana Hadarean, Dejan Jovanovic, Kshitij Bansal, Tianyi Liang, Nestan Tsiskaridze, Amit Goel, Sava Krstic, Leonardo de Moura, Viktor Kuncak, Jasmin Blanchette

- **Questions?**