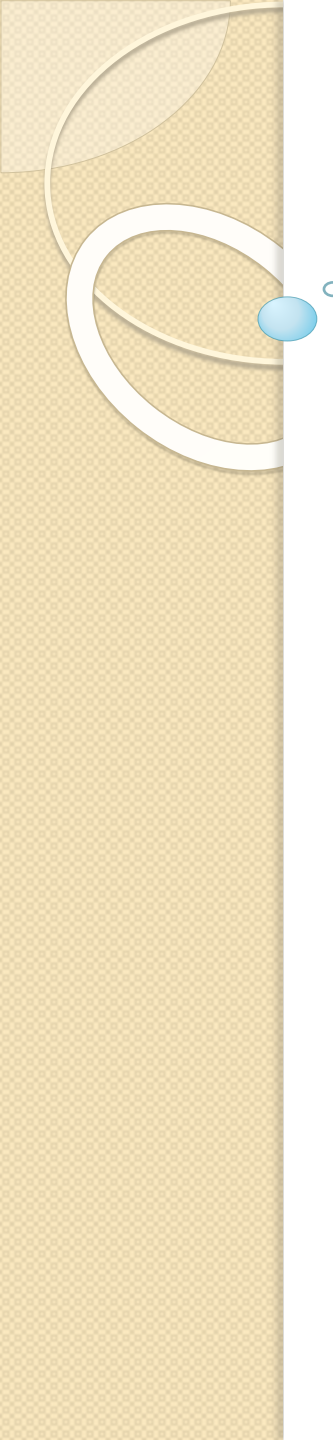


Guessing Game

I'm thinking of a research area where...

- Algorithms have recently improved by orders of magnitude
- Computers solve tasks better than humans
- Computers solve tasks without help from humans
- Big investments are being made by the government and companies like:
Amazon, Apple, Facebook, Google, Intel, Microsoft
- It can be described using two letters; first one is A



Automated Reasoning and the future of Formal Methods

Clark Barrett
Stanford University

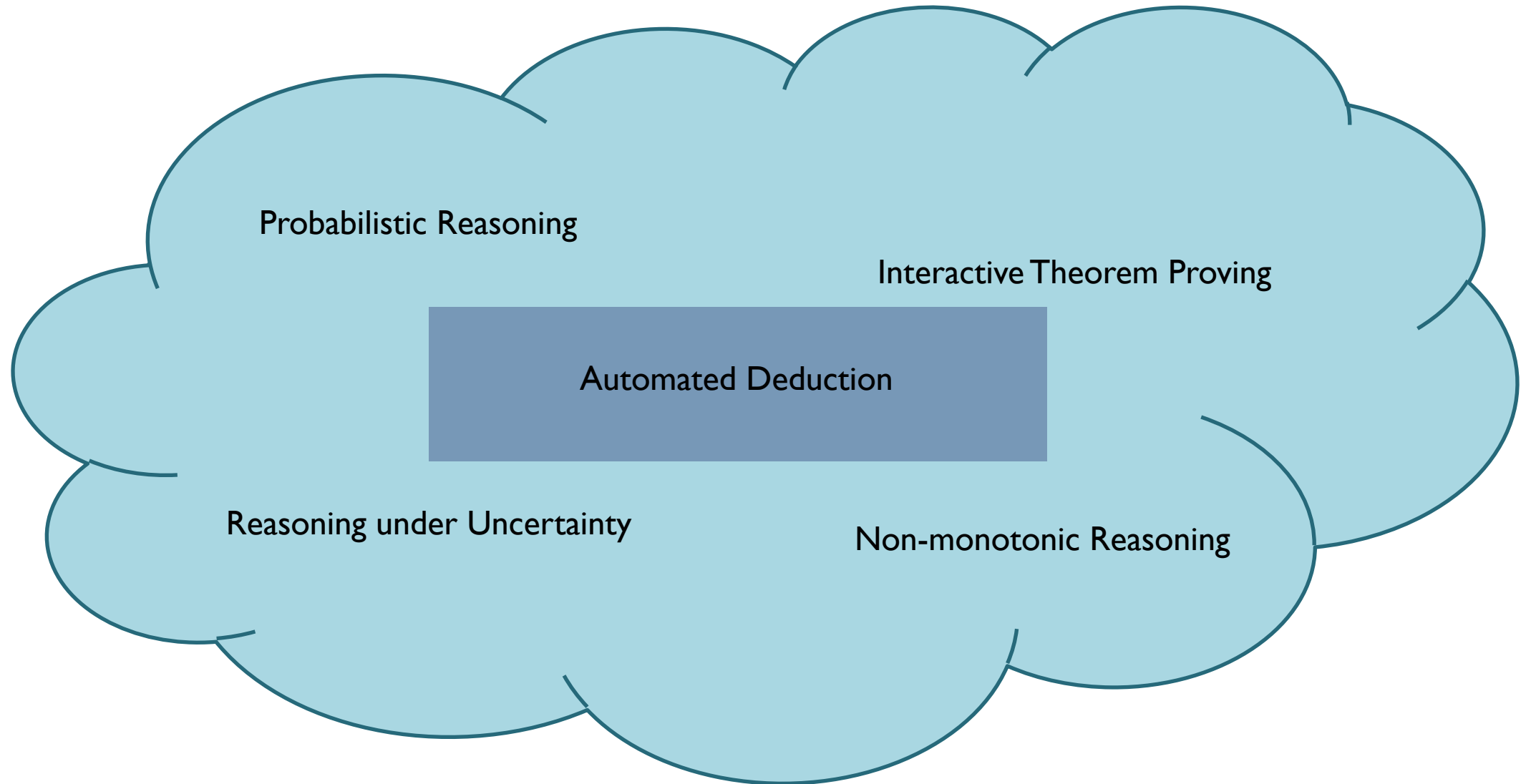
FM@Scale
October 9, 2019
SRI



Outline

- Improving Core AR Engines
- The Many Uses of Proofs
- Improving Usability

What is Automated Reasoning?



Automated Reasoning Engines

- Find p and q :
 - $(p \vee \neg q) \wedge (\neg p \vee q)$
 - *Boolean Satisfiability (SAT)*
 - The original NP-complete problem
- Prove or disprove:
 - $\exists x. (P(x) \rightarrow \forall y. P(y))$
 - *Automated Theorem Proving (ATP)*
 - Pure first-order logic
 - Semi-decidable
- Find a solution:
 - $a = b + 2 \wedge A = \text{write}(B, a + 1, 4) \wedge (A[b + 3] = 2 \vee f(a - 1) \neq f(b + 1))$
 - *Satisfiability Modulo Theories (SMT)*
 - Language includes Boolean logic, first-order logic, and certain built-in theories
 - Theory examples: arithmetic, arrays, functions, bitvectors, strings, sets, etc.
 - From NP-complete to undecidable

What is Automated Reasoning Good For?

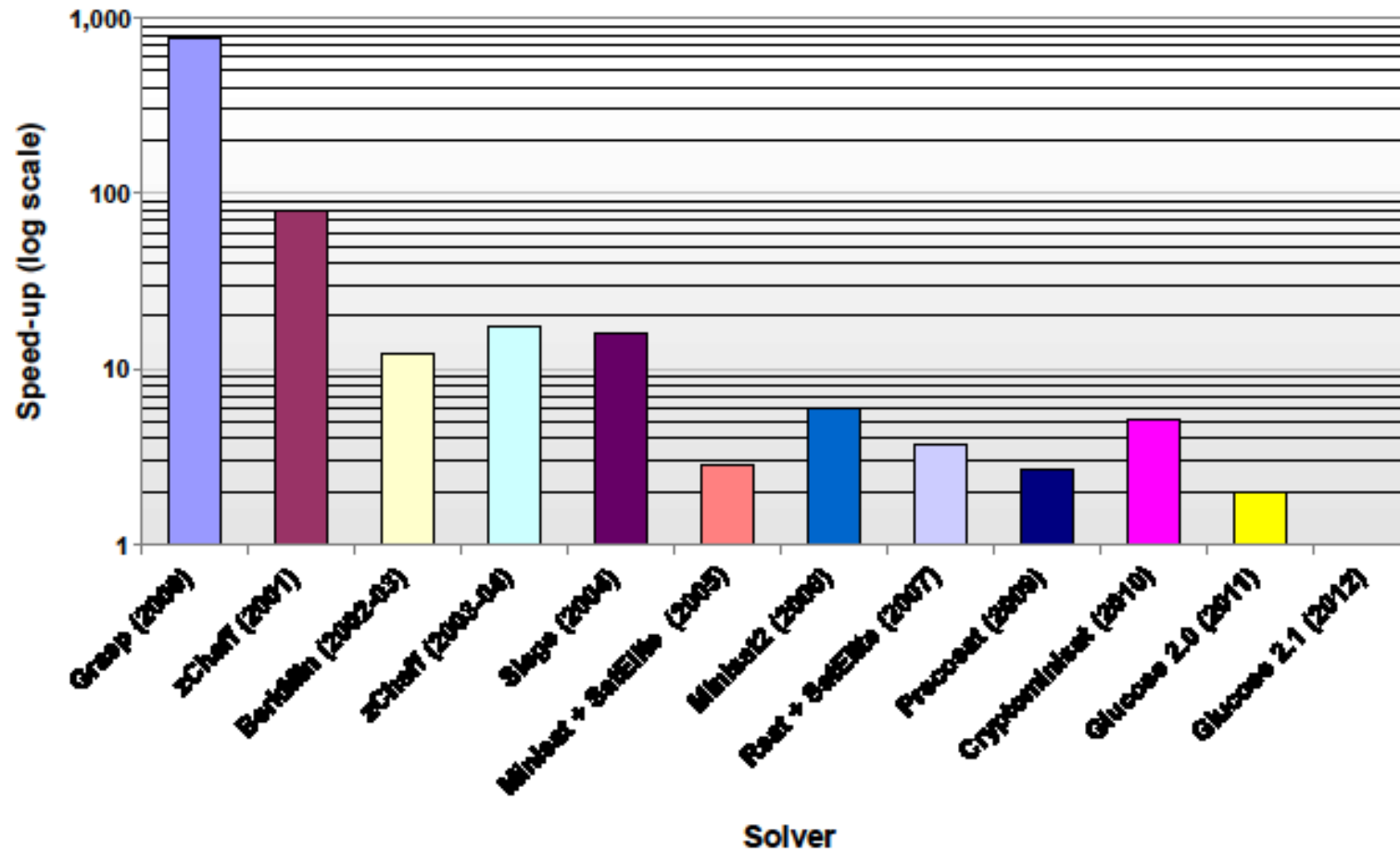
- Used for lots of things, but one big success is when coupled with *formal methods* to check whether a system conforms to some desired property
- **Safety**
 - Critical systems don't fail catastrophically
- **Security**
 - Systems are free from vulnerabilities
- **Verification**
 - Systems behave as intended

New Capabilities of Automated Reasoning

- *Faster*
 - Off-the shelf performance of tools has increased by orders of magnitude
- *Stronger*
 - More deductive power in modern tools (e.g. increasing number of supported theories in SMT solvers)
- *Better*
 - Flexible, adaptable, extensible – modern AR platforms can be modified for new challenging problems

Some Experience with SAT Solving

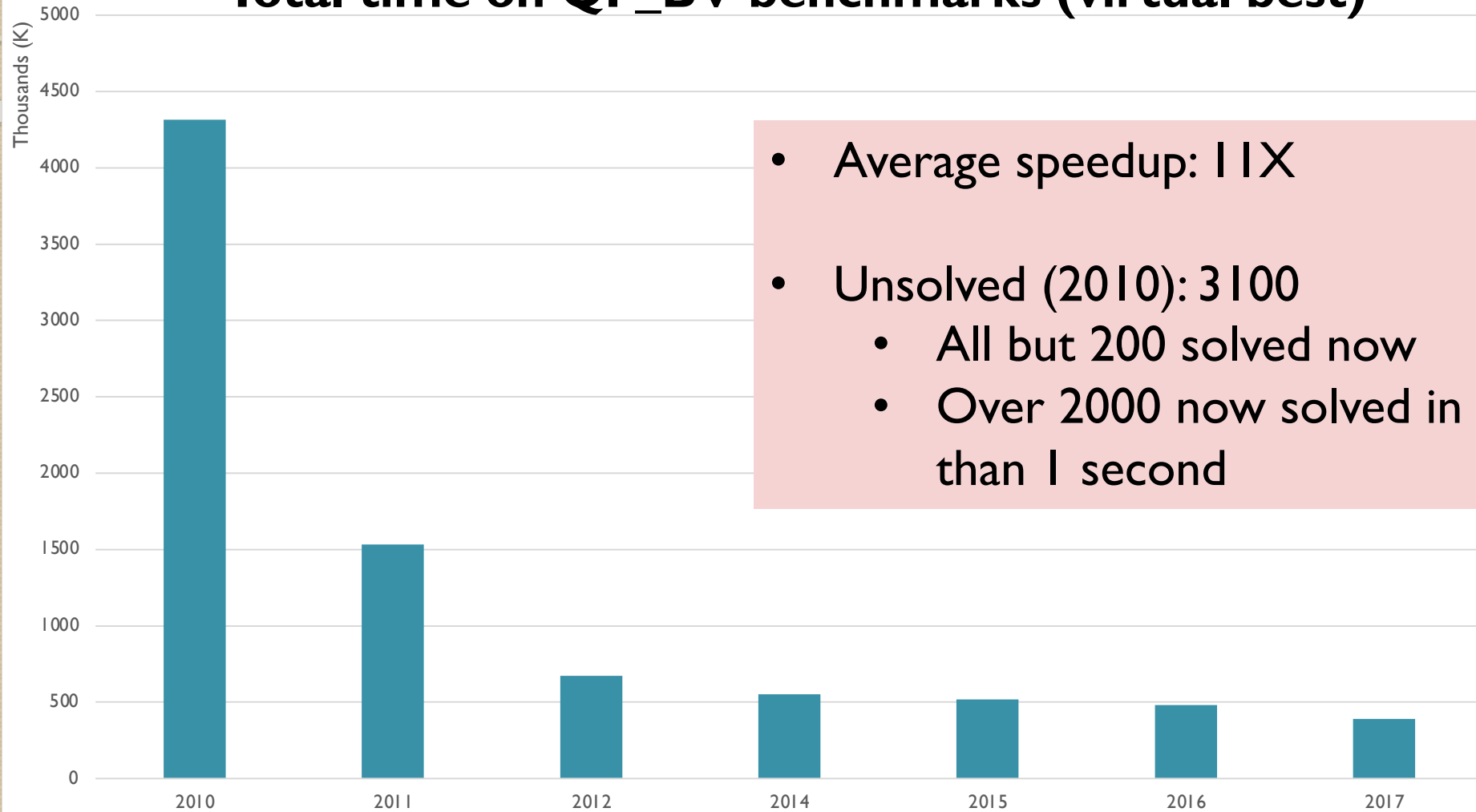
Speed-up of 2012 solver over other solvers



6

Evolution of SMT Solving

Total time on QF_BV benchmarks (virtual best)



- Average speedup: 11X
- Unsolved (2010): 3100
 - All but 200 solved now
 - Over 2000 now solved in less than 1 second

Automated Reasoning: Opportunities

- Core engines can still improve *dramatically*
- Need more people *developing* AR engines
 - Fund system-building proposals in AR!
 - Competition for new tools?
- Co-evolve engines with applications
 - Example: verification of neural networks
- Pursue parallelization
 - Some promising directions in SAT (cube and conquer)
- Use machine learning to tune configurations and strategies

Automated Reasoning: Opportunities

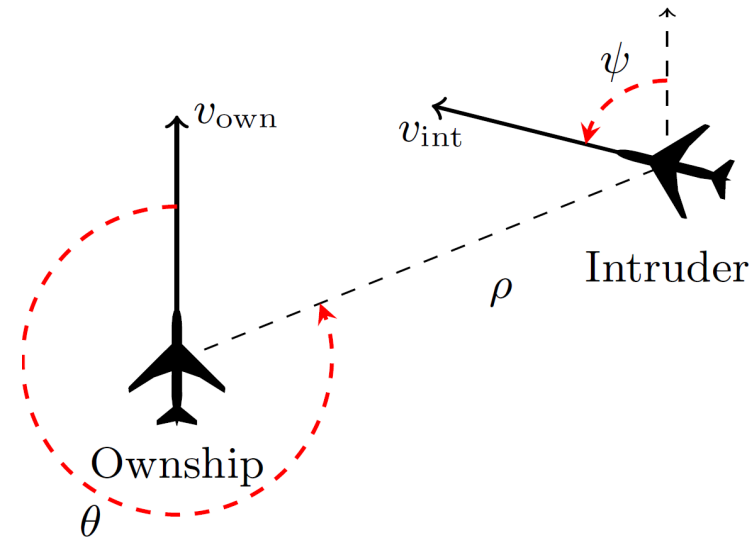
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Motivation: ACAS Xu

- Airborne Collision-Avoidance System for drones
- A new standard being developed by the FAA

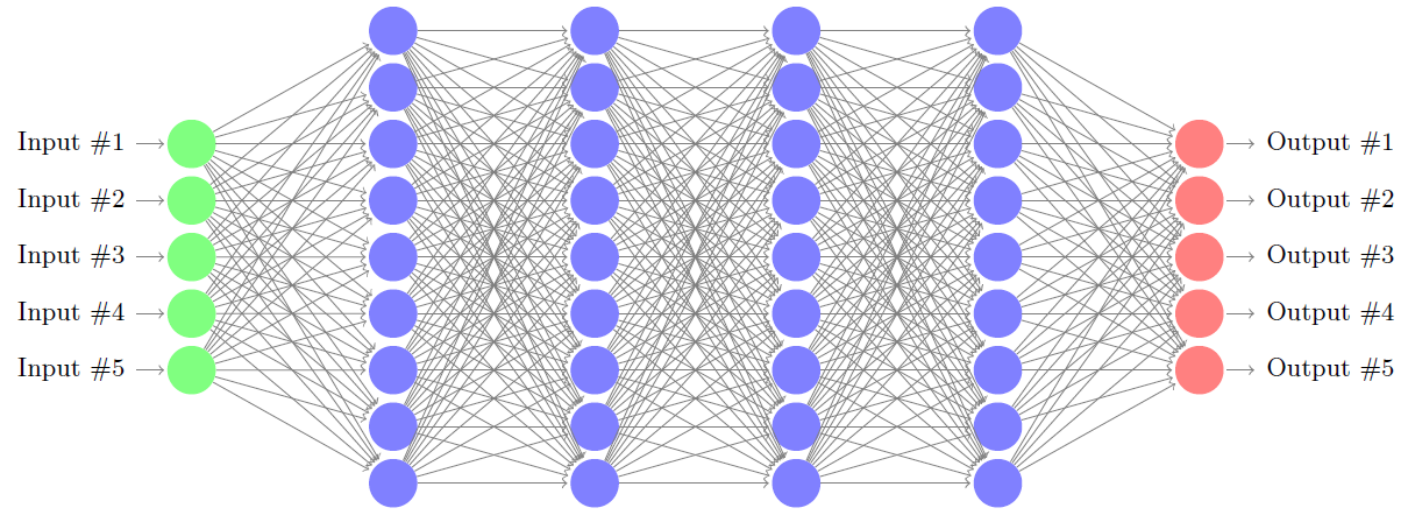
- Produce advisories:

1. Strong left (SL)
2. Weak left (L)
3. Strong right (SR)
4. Weak right (R)
5. Clear of conflict (COC)



- Best-performing implementation uses 45 deep neural networks
 - How do we verify them?

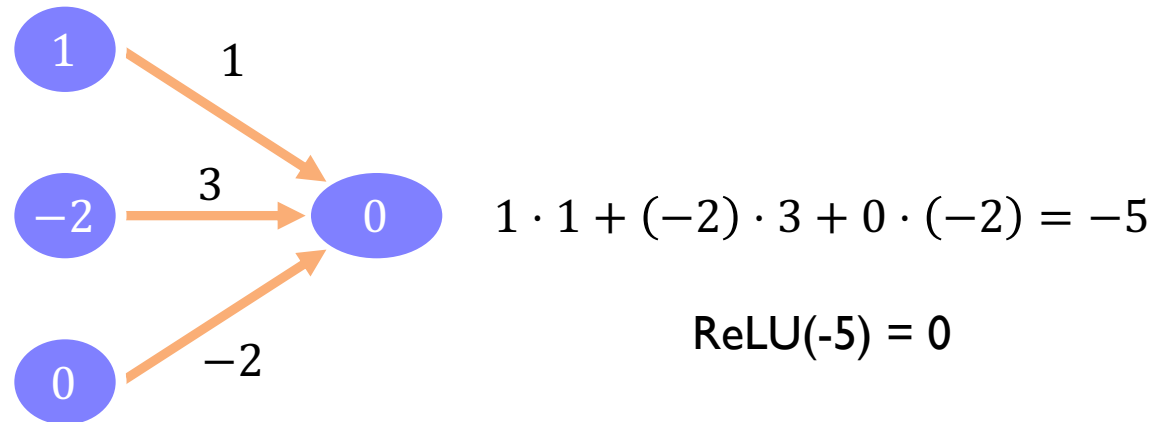
Deep Neural Nets (DNNs)



- ACAS Xu networks: 8 layers, 310 nodes (x 45)
- Naïve translation to SMT scales to networks with ~20 nodes
- NP-Complete problem!

The Culprits: Rectified Linear Units (ReLU)

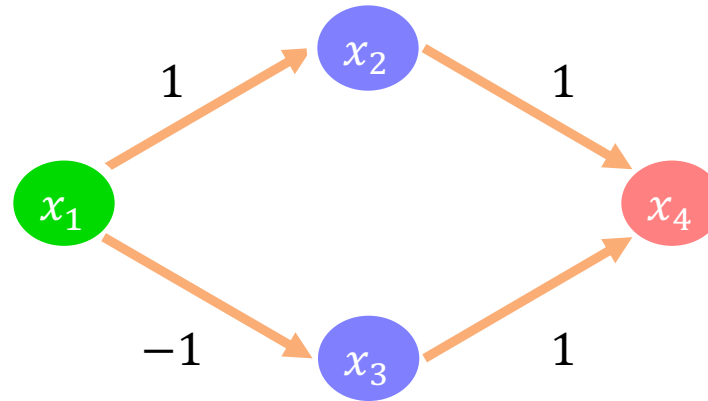
- $\text{ReLU}(x) = \max(0, x)$
 - $x \geq 0$: active case, return x
 - $x < 0$: inactive case, return 0
 - Example:



Reluplex: SMT Solver for Neural Networks

- A technique for solving linear programs with ReLUs
 - Can encode neural networks as input
- Extends the simplex method
- Does *not* require case splitting in advance
 - ReLU constraints satisfied incrementally
 - Split only if we must
- Scales to the ACAS Xu networks
 - An order of magnitude larger networks than previously possible

A Simple Example



- Property being checked:
Is it possible that $x_1 \in [0,1]$ and $x_4 \in [0.5,1]$?

Encoding Networks

- Introduce equalities:

$$x_2^w - x_1 = 0$$

$$x_3^w + x_1 = 0$$

$$x_4 - x_3^a - x_2^a = 0$$

- Set bounds:

$$x_1 \in [0,1]$$

$$x_4 \in [0.5,1]$$

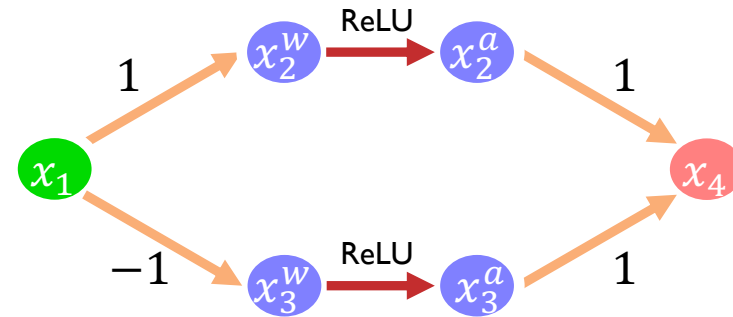
$$x_2^w, x_3^w \in (-\infty, \infty)$$

$$x_2^a, x_3^a \in [0, \infty)$$

- Special ReLU constraints:

$$x_2^a = \text{ReLU}(x_2^w)$$

$$x_3^a = \text{ReLU}(x_3^w)$$



Reluplex: Example

$$x_5 = x_2^w - x_5$$

$$x_6^w = x_2^w + x_6^w - x_2^w$$

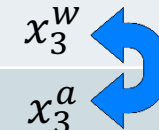
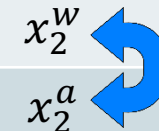
$$x_7^a = x_4 - x_3^a - x_7^a$$

Operation:

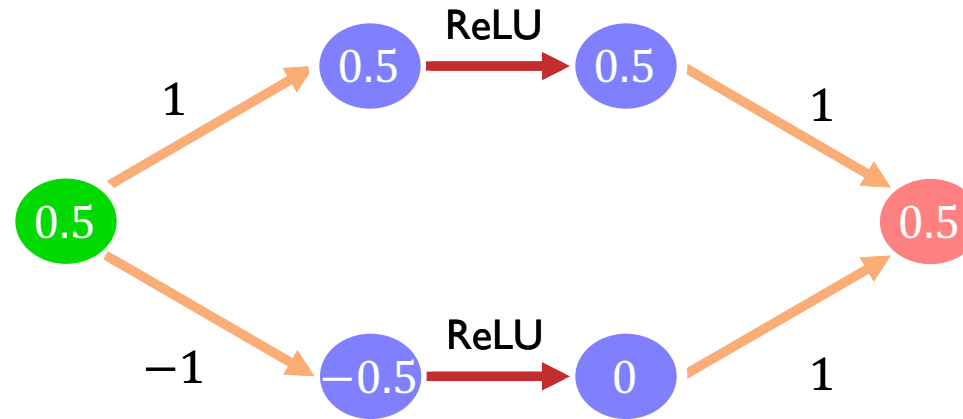
Success $x_2^w + 0.5$



Lower Bound	Variable	Assignment	Upper Bound
0	x_1	0.5	1
	x_2^w	0.5	
0	x_2^a	0.5	
	x_3^w	-0.5	
0	x_3^a	0	
0.5	x_4	0.5	1
0	x_5	0.5	0
0	x_6	0.5	0
0	x_7	0.5	0



The Assignment is a Solution



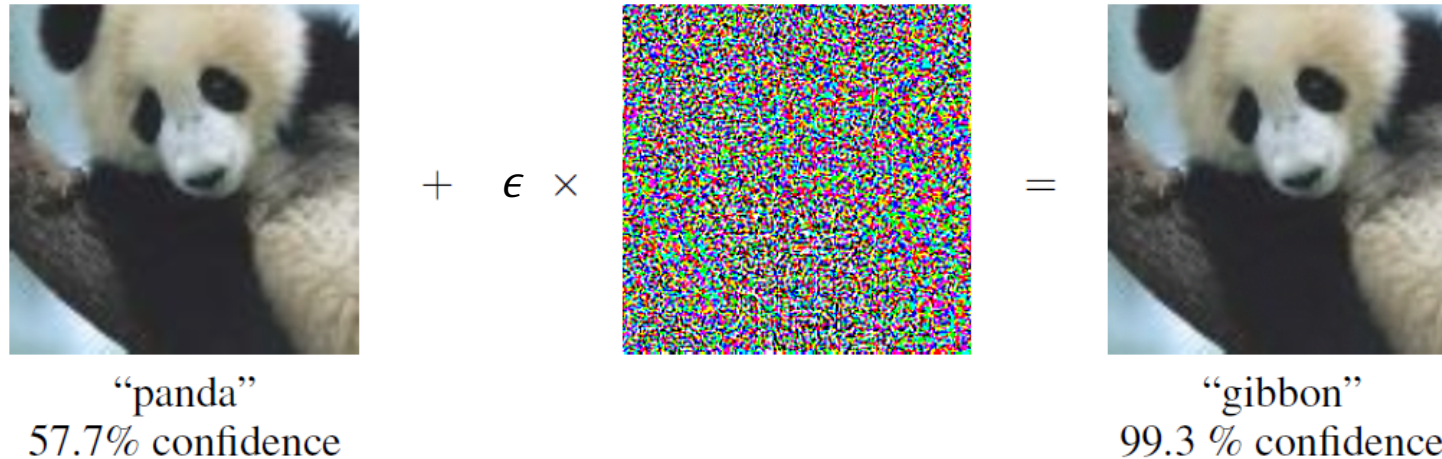
- Property being checked:
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Robustness to Adversarial Inputs

- Slight input perturbations cause misclassification

Goodfellow et al., 2015



- We can *prove* that these cannot occur (for given input and amount of noise)



Outline

- Improving Core AR Engines
- The Many Uses of Proofs
- Improving Usability

Who Watches

The **WATCHMEN?**



The Need for Proofs

- If an AR engine returns a model/counter-example, it can be checked
- But if it returns unsatisfiable, the result has to be trusted
- ...unless the tool can produce an independently-checkable proof
- There is already a standard for SAT solvers

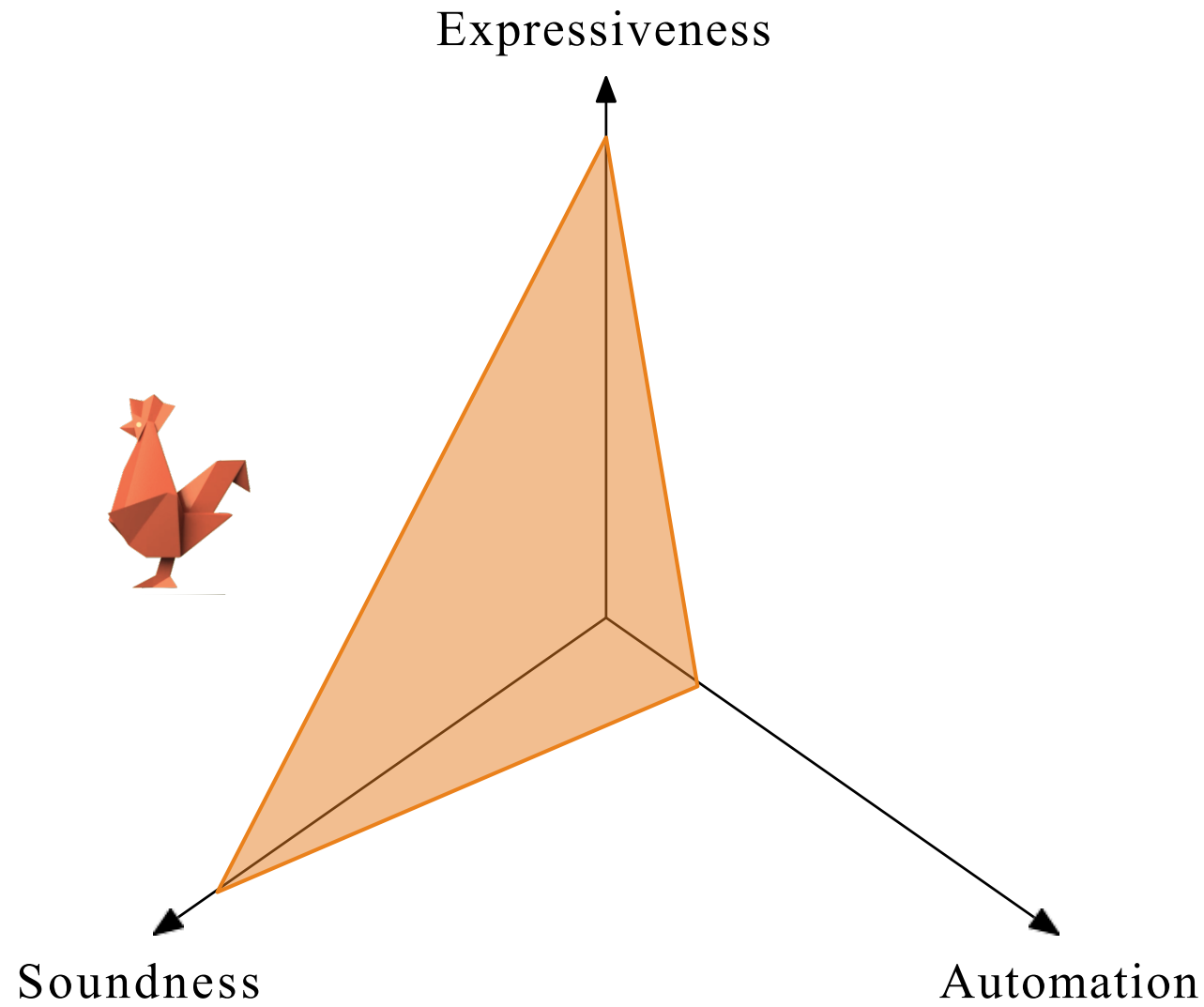
What are Proofs good for?

- Reducing the trusted code base
- Improving code quality of AR engines
- *Trusted* interoperability with other tools
- Can be mined for additional information (e.g. interpolants)
- Auditable trail for building assurance cases

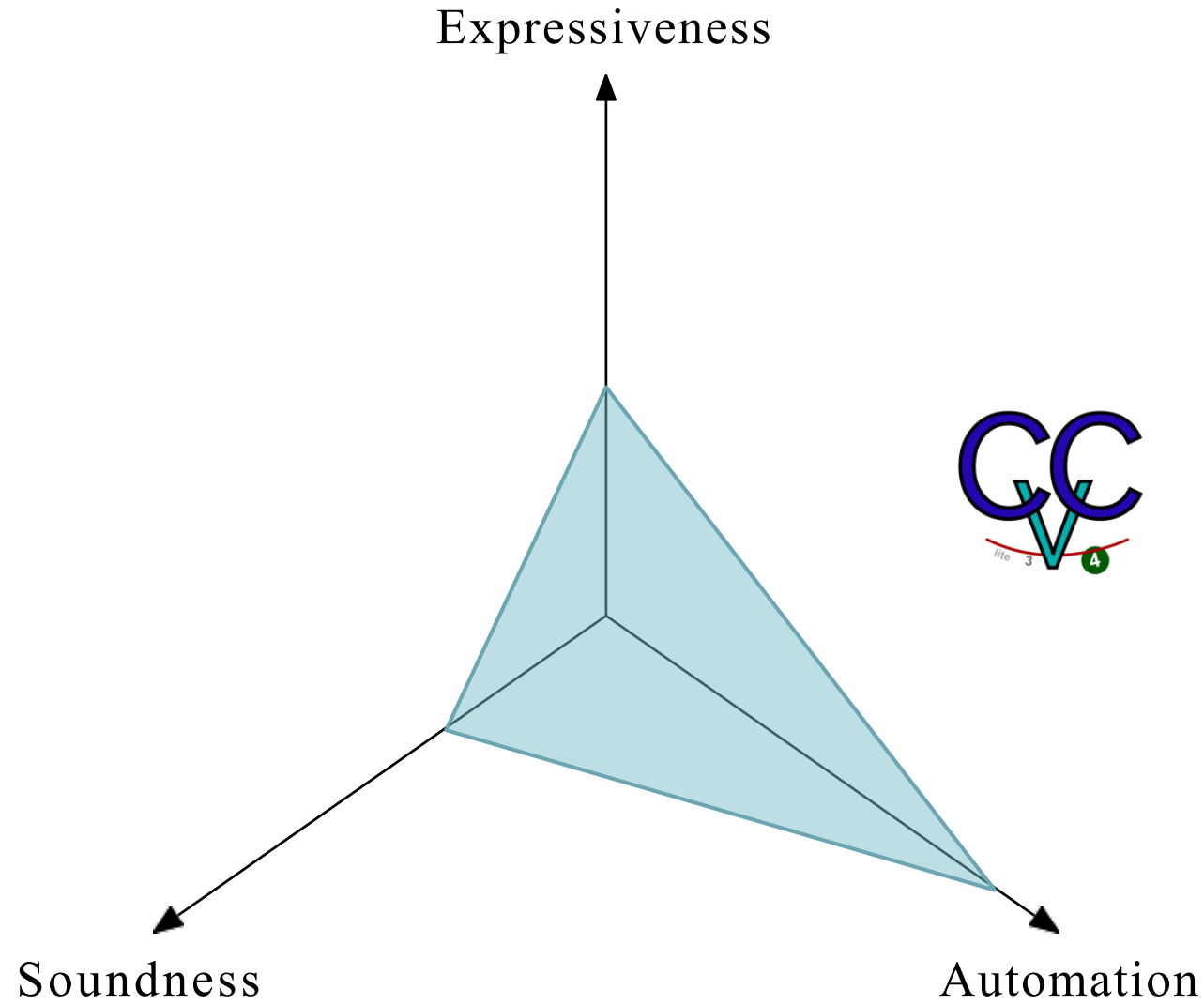
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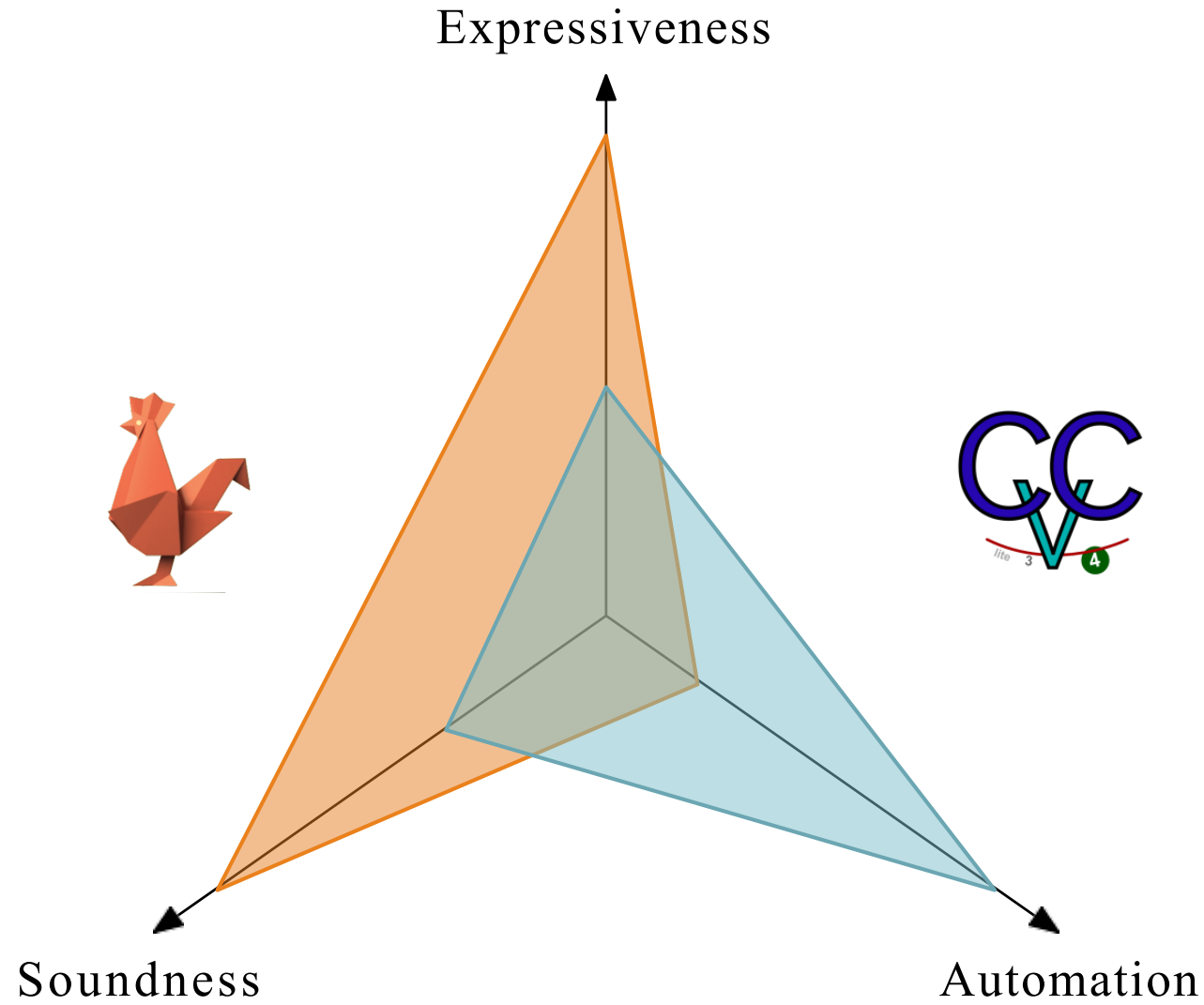
Proof assistants vs SMT solvers

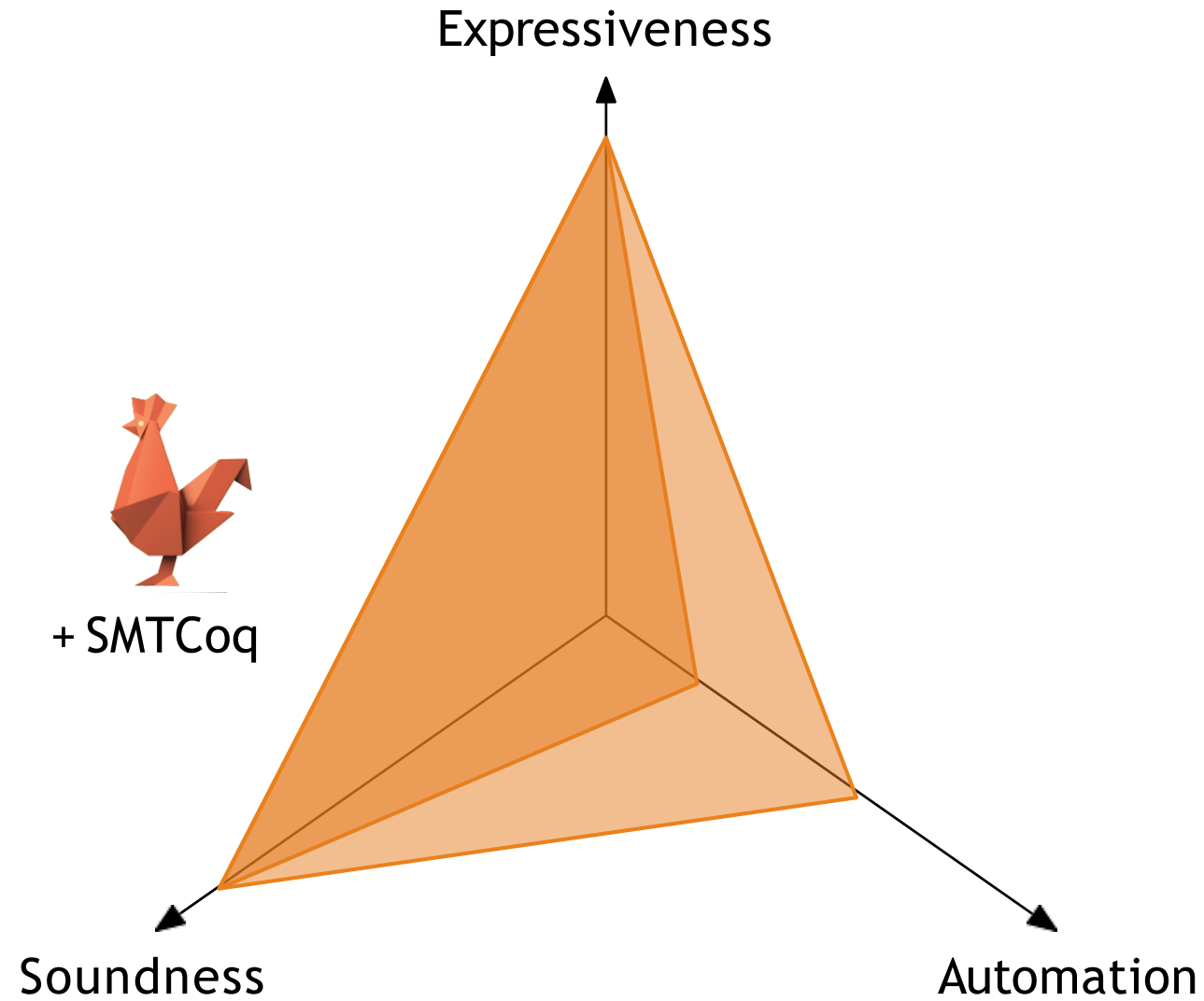


Proof assistants vs SMT solvers

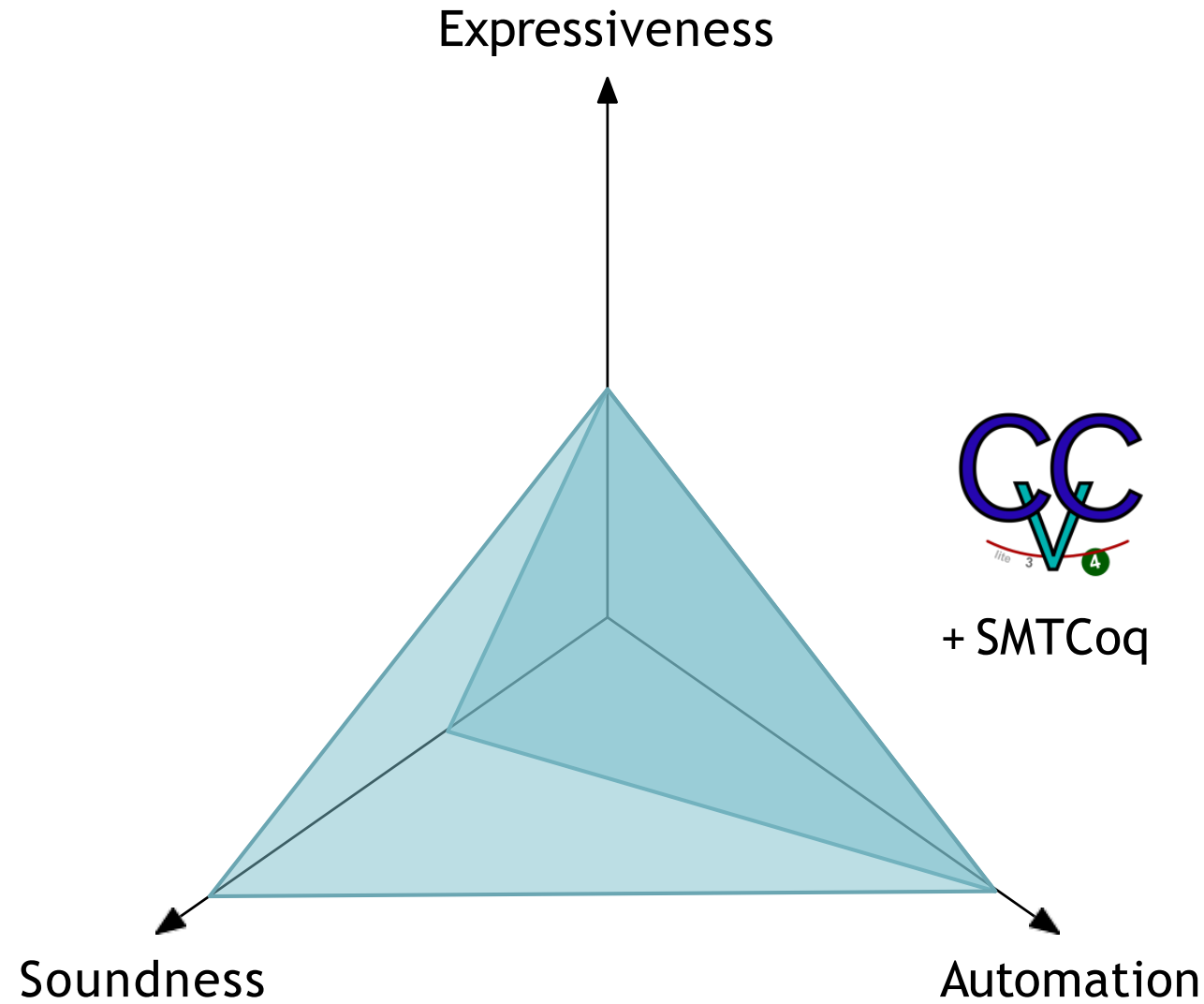


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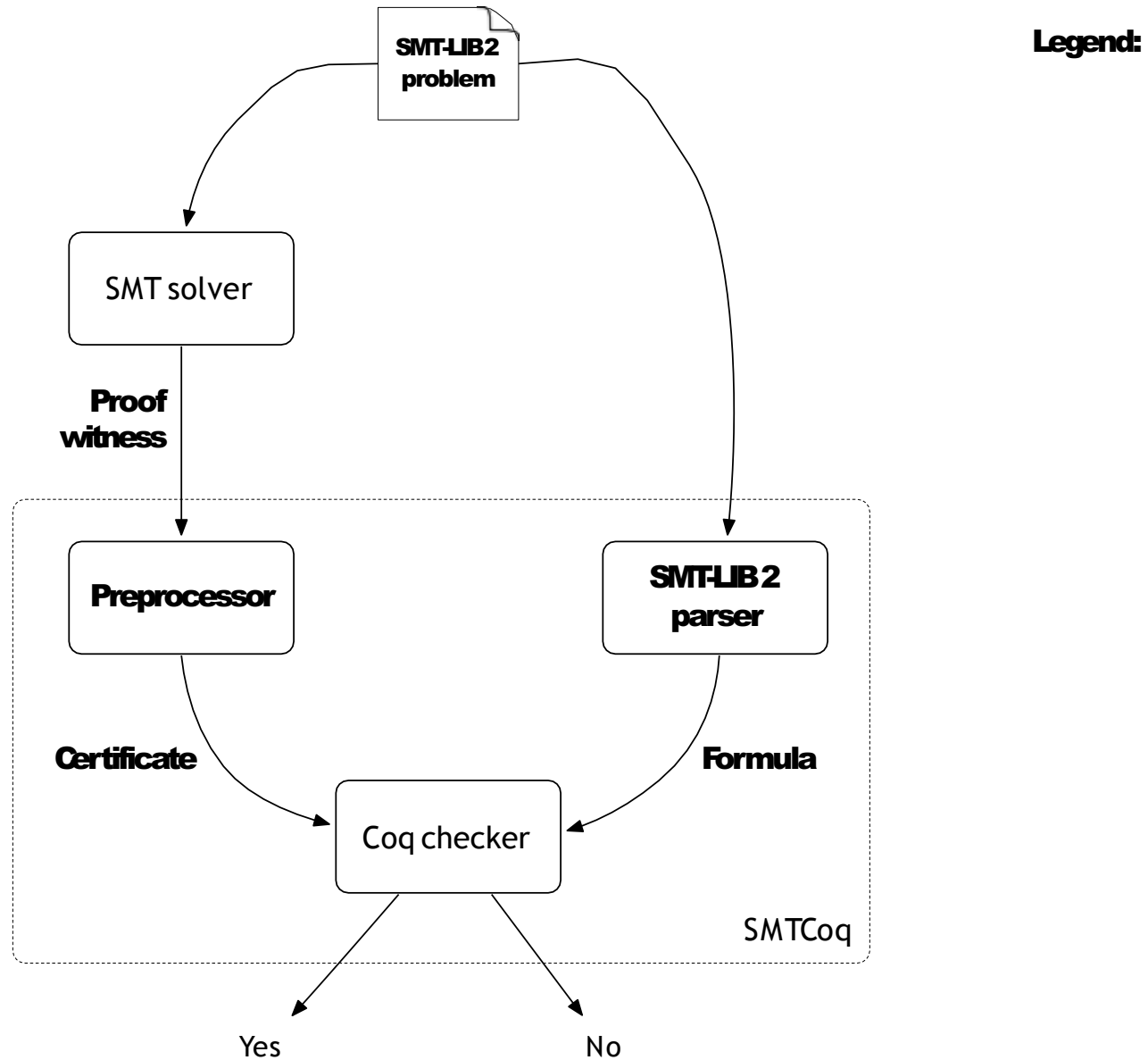




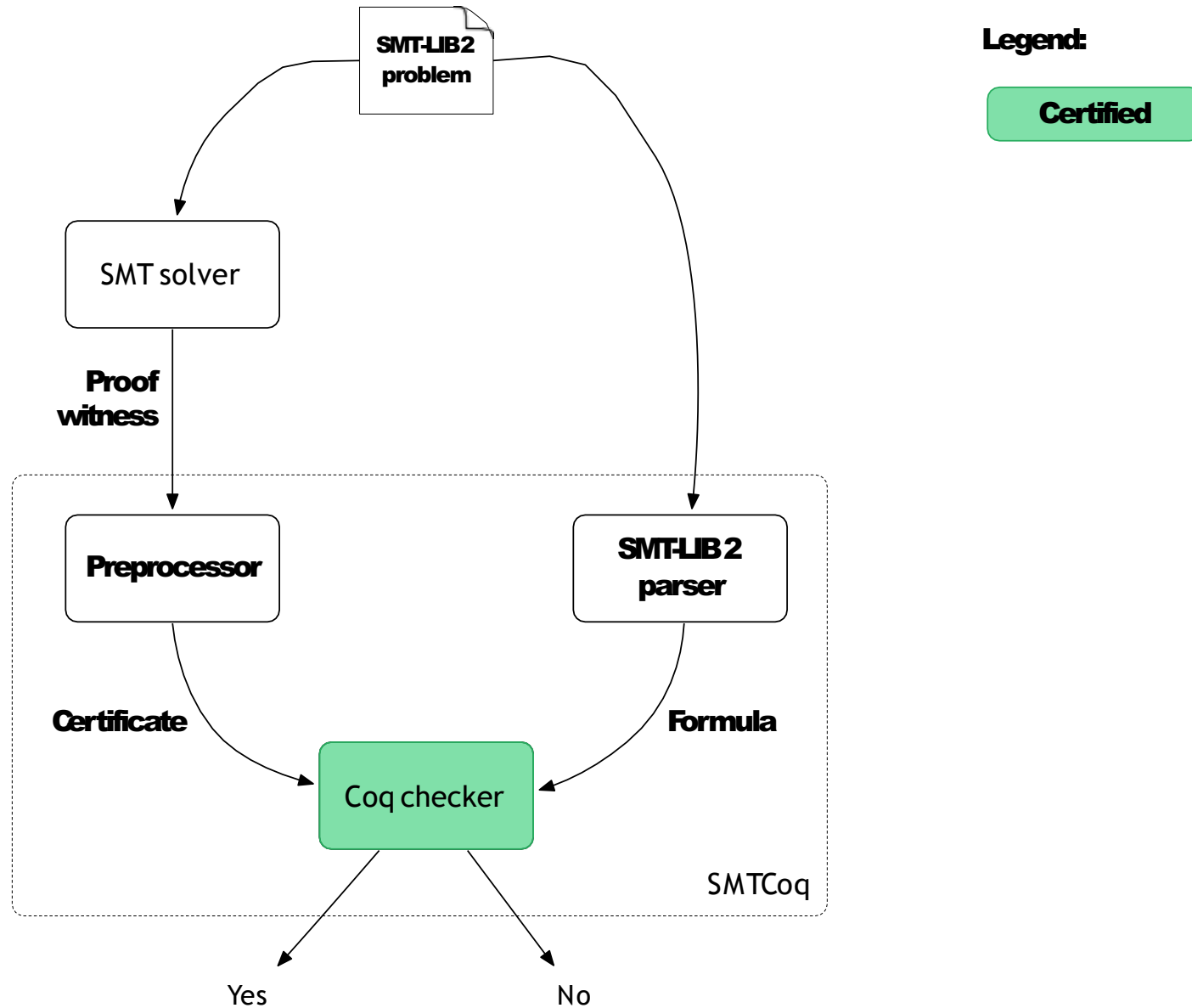
Effects of SMTCoq as a proof checker



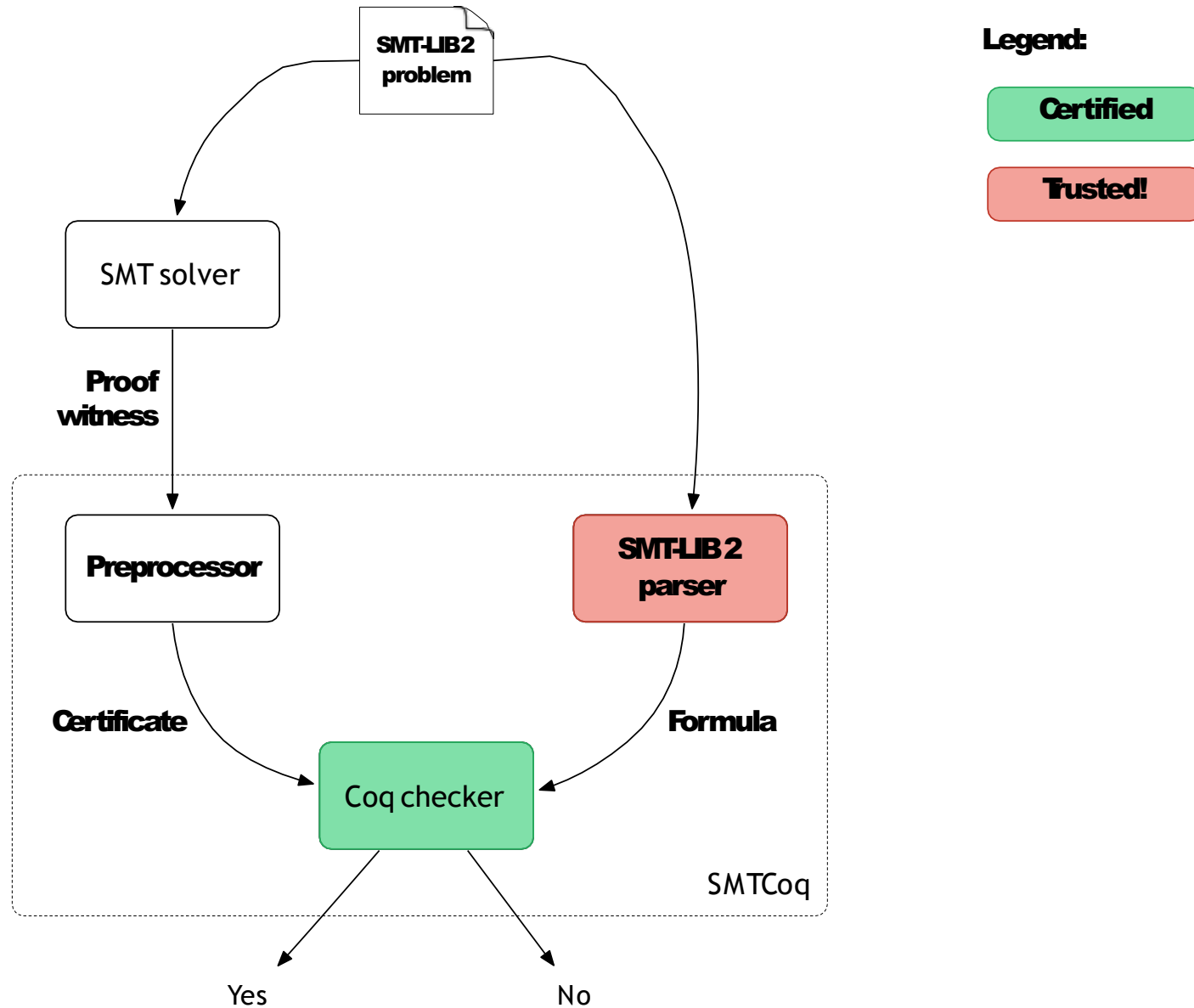
SMTCoq as a stand-alone checker



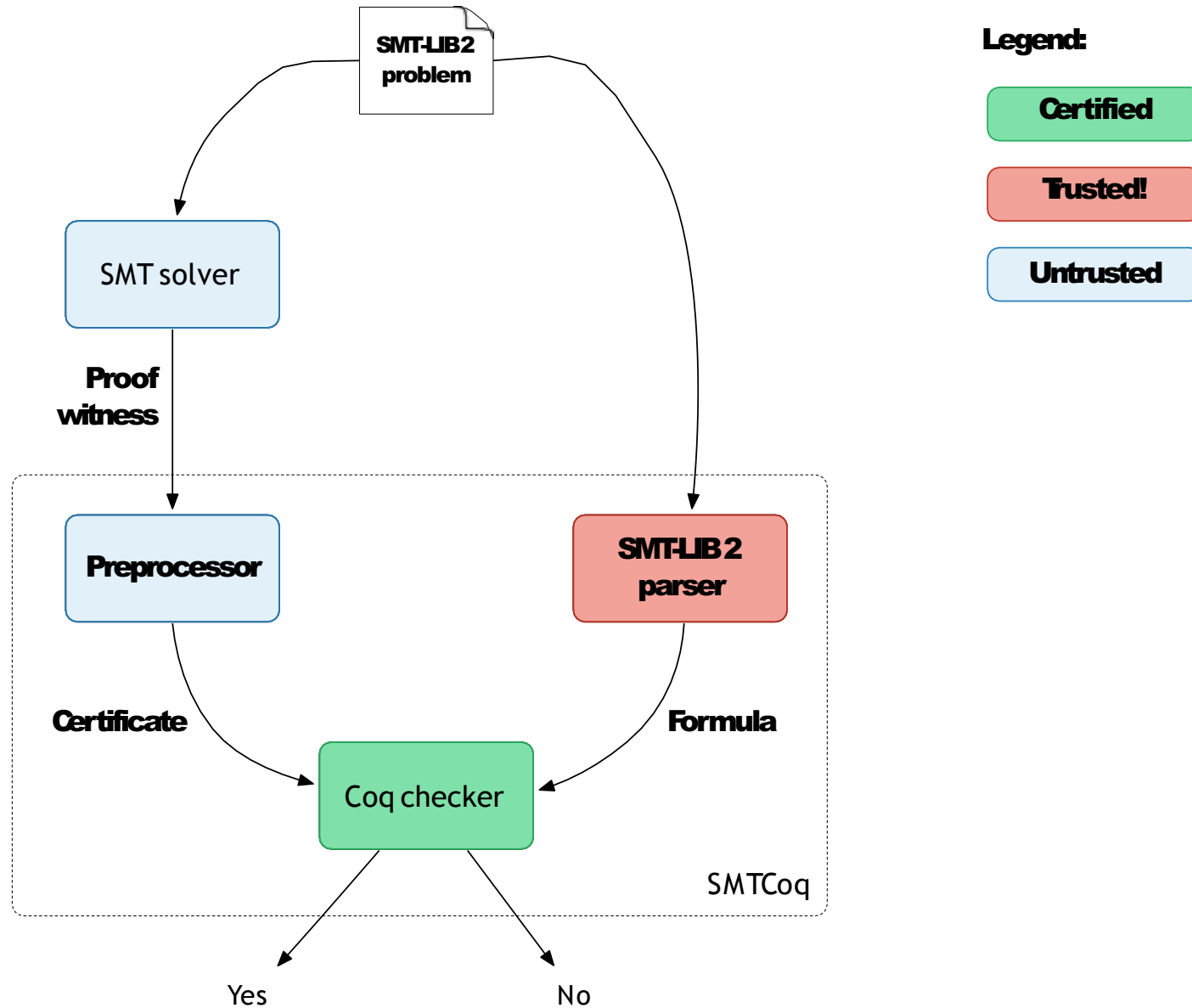
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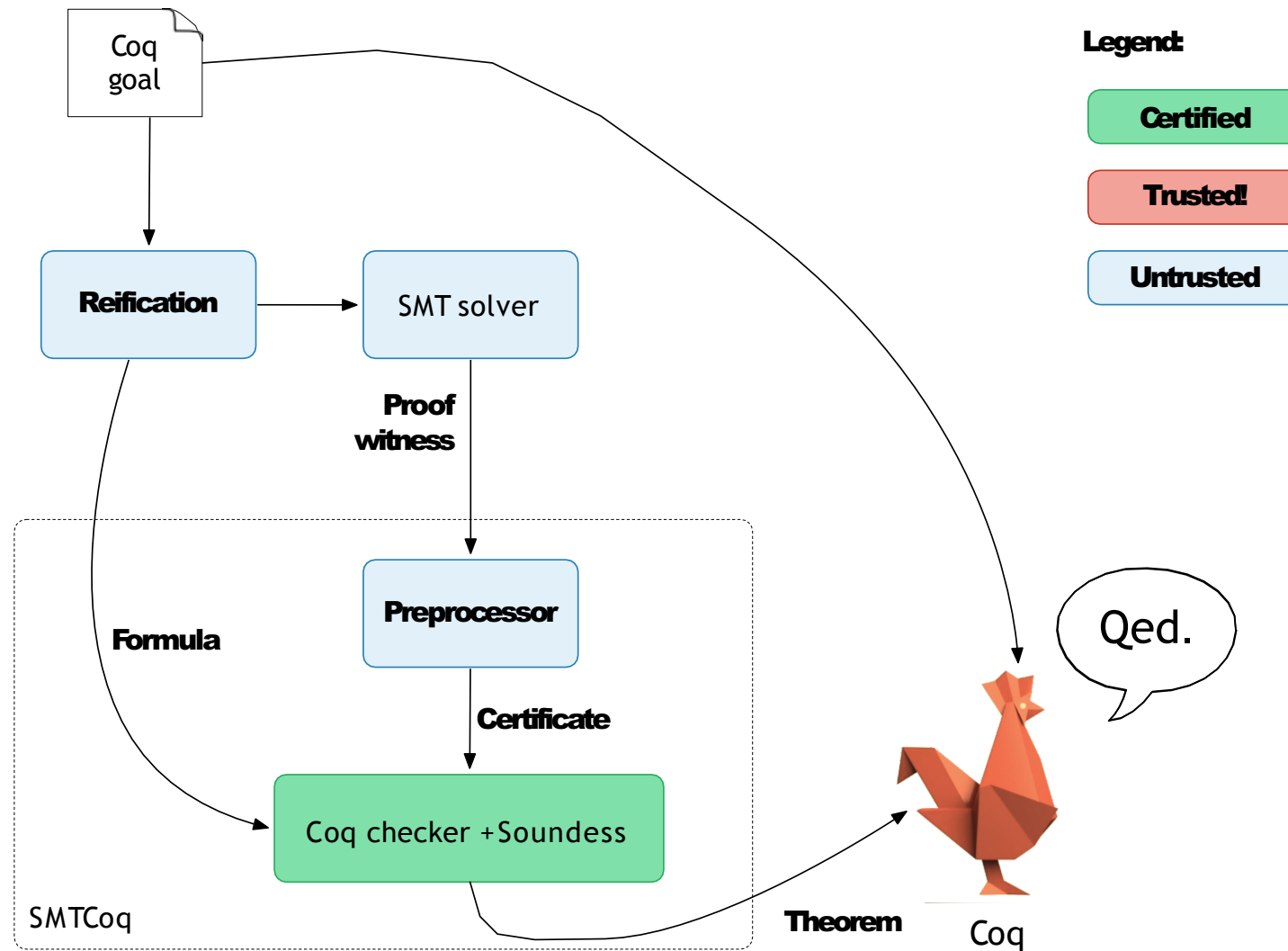
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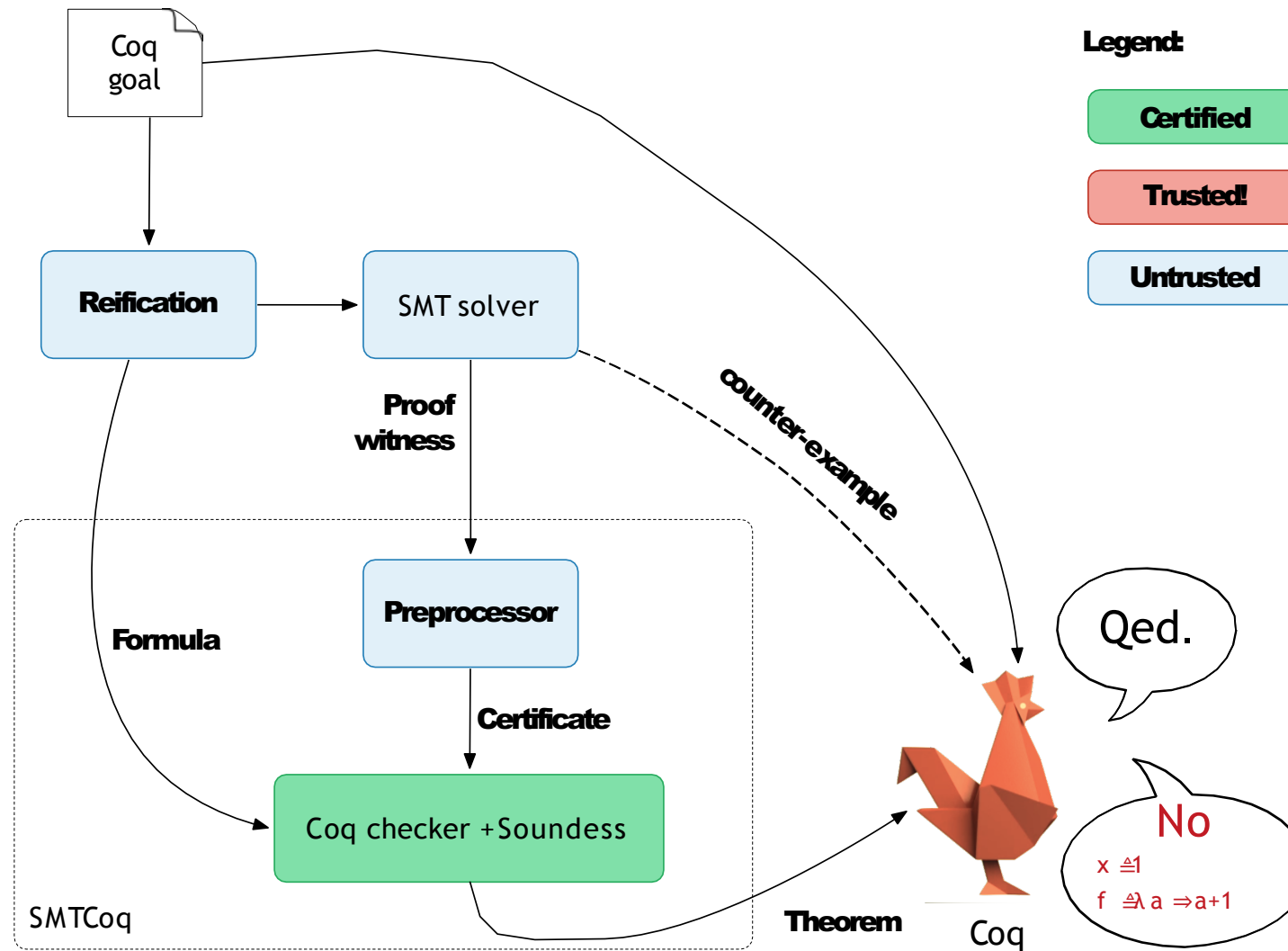
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SMTCoq from within Coq



SMTCoq from within Coq





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The Usability Challenge

- Experts can do great things with formal tools
- Need to find more ways for non-experts to benefit from formal tools
- Develop Tools and Techniques that use formal under the hood but expose a simple interface for users

The Usability Challenge

- Experts can do great things with formal tools
- Need to find more ways for non-experts to benefit from formal tools
- Develop Tools and Techniques that use formal under the hood but expose a simple interface for users
 - Example: Symbolic QED for hardware verification

Quick Error Detection

QED

- Technique developed by *Subhasish Mitra*'s group
- Key idea
 - Use regular and shadow values for registers and memory
 - Apply *duplicate and check* transformation to improve tests

Quick Error Detection

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Example

	Regular	Shadow
Registers	R0...R15	R16...R31
Memory	0x10000 – 0x1FFFF	0x20000 – 0x2FFFF

Quick Error Detection

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Example

	Regular	Shadow
Registers	R0...R15	R16...R31
Memory	0x10000 – 0x1FFFF	0x20000 – 0x2FFFF

```
...
LD R1, [0x10000]
LD R2, [0x10040]
...
LD R1, [0x10000]
LD R2, [0x10040]
...
LD R17, [0x20000]
LD R18, [0x20040]
CMP R1 == R17
CMP R2 == R18
```

Quick Error Detection

QED features

- Improves *coverage* and *speed* of bug detection with respect to standard testing
- Reduces *error latency* (time between when bug is activated and detected)

QED limitations

- *Not exhaustive* - might miss bugs
- Error latency can still be *hundreds of instructions*

Quick Error Detection

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Idea

46

- Combine QED with *Bounded Model Checking*

Symbolic QED

Result: *Symbolic QED*

- Collaboration with Subhasish Mitra's group ¹³
- *Idea*: use BMC to search through *all possible* QED tests
 - Initial state: *QED-consistent* (regular and shadow values match)
 - Input must be sequence of regular instructions followed by duplicate instructions
 - Property: *final state must be QED-consistent*

Addresses limitations of QED

- Exhaustively covers *all possible* QED tests
- Finds *minimum length* QED test that triggers bug

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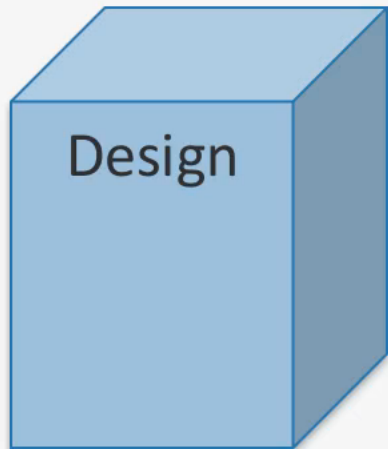
A GENERIC APPROACH TO SYMBOLIC QED



Designer Hat: Fill out Template Format File

ISA/Design
Format File

Demo:
RIDECORE (RISC-V)



**THE ELECTRONICS
RESURGENCE INITIATIVE**

Conclusions

- Improvements in core AR engines have big payoffs
- Significant progress can be made by evolving engines driven by new applications
 - But need to build more talent and expertise in solver development
- An ecosystem of interchangeable proofs would enable high-trust interoperability
- Need to find creative ways to make formal power accessible to non-experts

Backup: Proving and Satisfying

- A formula is a theorem iff its negation is not satisfiable:

$$\models \Phi \iff \neg\Phi \text{ is unsatisfiable}$$

- Theorem proving and satisfiability checking are dual

Backup: Case Splitting

- Linear programs (LPs) are easy to solve
- Piecewise-linear constraints are reducible to LPs
- Case Splitting:
 - Fix *each* ReLU to active or inactive state
 - Solve the resulting LP
 - If solution is found, we are done
 - Otherwise, backtrack and try other option
- State explosion: 300 ReLUs $\rightarrow 2^{300}$ checks

Backup: Soundness & Termination

- Soundness is straightforward
- Can we always find a solution using pivots and updates?
- No: sometimes get into a loop
- May have to *split* on ReLU variables
 - Do so *lazily*
 - In practice, about 10% of the ReLUs