# Case Story: Trust and Cloud

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Introduction

Automated Reasoning and Satisfiability

Trusted Computing

Reasoning in the Cloud

Conclusions and Challenges

# Introduction

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# "The Largest Math Proof Ever" engadget



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#### 4 CPU years computation, but 2 days on cluster (800 cores)

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4 CPU years computation, but 2 days on cluster (800 cores) 200 terabytes proof, but validated with verified checker

# **Computer-Aided Mathematics**

Fields Medalist Timothy Gowers stated that mathematicians would like to use three kinds of technology [Big Proof 2017]:

- Proof Assistant Technology
  - Prove any lemma that a graduate student can work out
- Proof Search Technology
  - Automatically determine whether a conjecture holds
  - In this talk: Linear speedups on thousands of cores
- Proof Checking Technology
  - Mechanized validation of all details
  - In this talk: Formally verified checking of huge proofs



# Automated Reasoning and Satisfiability

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# Automated Reasoning Has Many Applications



# Automated Reasoning Has Many Applications



# Breakthrough in SAT Solving in the Last 20 Years

Satisfiability (SAT) problem: Can a Boolean formula be satisfied?

mid '90s: formulas solvable with thousands of variables and clauses now: formulas solvable with millions of variables and clauses





Edmund Clarke: *"a key* technology of the 21st century" [Biere, Heule, vanMaaren, and Walsh '09]

Donald Knuth: "evidently a killer app, because it is key to the solution of so many other problems" [Knuth '15]

# Progress of SAT Solvers



Results of the SAT competition/race winners on the SAT 2009 application benchmarks, 20mn timeout

Recent Advances at SAT Competitions

Dozens of solvers participate in the annual SAT competition

A new idea contributes to winning the competition

Winner 2017: Clause minimization during search [Luo, Li, Xiao, Manyá, and Lü 2017]

Winner 2018: Chronological backtracking [Nadel and Ryvchin 2018]

Winner 2019: Multiple learnt clauses per conflict [Kochemazov, Zaikin, Kondratiev, and Semenov 2019]

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# Motivation

Automated reasoning tools may give incorrect answers.

- Documented bugs in SAT, SMT, and QSAT solvers; [Brummayer and Biere, 2009; Brummayer et al., 2010]
- Claims of correctness could be due to bugs;
- Misconception that only weak tools are buggy;
- Implementation errors often imply conceptual errors;
- Proofs now mandatory in some competitive events;
- Mathematical results require a stronger justification than a simple yes/no by a tool. Answers must be verifiable.

# Verified Solving versus Verified Proofs

Verifying efficient automated reasoning tools is a daunting task:

- Tools are constantly modified and improved; and
- Even top-tier and "experimentally correct" solvers turned out to be buggy. [Järvisalo, Heule, Biere '12]

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Various simple solvers can verified, but they lack performance

- DPLL [Shankar and Vaucher '11]
- CDCL [Fleury, Blanchette, Lammich '18]

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Validating proof is the more effective approach

- Solving + proof logging + proof verification is much faster compared to running a verified solver
- One verified tool can validate the results of many solvers

# Initial Challenges

Theoretical challenges:

- Some "simple" problems have exponentially large proofs in the resolution proof system [Urquhart '87, Buss and Pitassi '98];
- While some dedicated techniques can quickly solve them.

Solution: A proof system to compactly express all techniques.

# Initial Challenges

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Solution: A proof system to compactly express all techniques.

Practical challenges:

- Earlier efforts failed due to complexity and overhead
- Convince developers to support proof logging

#### Solution:

- The computational burden and complexity is in the checker
- A reference implementation of proof logging

# Arbitrarily Complex Solvers

Verified checkers of certificates in strong proof systems:

- Don't worry about correctness or completeness of tools;
- Facilitates making tools more complex and efficient; while
- Full confidence in results. [Heule, Hunt, Kaufmann, Wetzler '17]



Formally verified checkers now also used in industry

Formally-Verified SAT Solving Tool Chain



Formally-Verified SAT Solving Tool Chain



- The validate step uses a formally-verified checker;
- Ideally the encoding step is also formally-verified;
- The other steps can be heavily optimized and unverified.

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# Dealing with Enormous Case Splits

What makes a problem hard?

The numbers angle: how many cases need to be explored?

The Four Color Theorem: Every map is colorable with 4 colors!

- Hard for humans as many cases need to be considered
- Computers can systematically check them all



 $www.cs.cmu.edu/{\sim}bryant/boolean/US48\_colored\_balance.jpg$ 

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Some hard problems have a trillion or more cases How to effectively parallelize computations?

# SAT Solver Paradigms

Conflict-driven clause learning (CDCL): Makes fast decisions and converts conflicting assignments into learned clauses. Strength: Effective on large, "easy" formulas. Weakness: Hard to parallelize.

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Look-ahead: Aims at finding a small binary search-tree by selecting effective splitting variables via looking ahead. Strength: Effective on small, hard formulas. Weakness: Expensive.

# Portfolio Solvers

The most commonly used parallel solving paradigm is portfolio:

- Run multiple (typically identical) solvers with different configurations on the same formula; and
- Share clauses among the solvers.



The portfolio approach is effective on large "easy" problems, but has difficulties to solve hard problems (out of memory).

Cube-and-Conquer [Heule, Kullmann, Wieringa, and Biere '11]

Cube-and-conquer splits a given problem into millions of subproblems that are solved independently by CDCL.



Efficient look-ahead splitting heuristics allow for linear speedups even when using 1000s of cores.

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Cube-and-conquer recently integrated in Z3

#### The Hidden Strength of Cube-and-Conquer

Let N denote the number of leaves in the cube-phase:

- the case N = 1 means pure CDCL,
- and very large N means pure look-ahead splitting.

Consider the total run-time (y-axis) in dependency on N (x-axis):

- typically, first it increases, then
- it decreases, but only for a large number of subproblems!



Example with Schur Triples and 5 colors: a formula with 708 vars and 22608 clauses.

The performance tends to be optimal when the cube and conquer times are comparable.

# Reasoning in the Cloud

Automated reasoning as a service:

- Solves problems from easy to hard;
- Can provide correctness proofs;
- Explains the solution and/or method.

Joint work with Siemens to fully explore the design space of gearboxes.

# SIEMENS

The NFL would like to have a cloud service to produce their schedules and they provided interesting test cases.





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# Conclusions and Challenges

We can have full confidence in the correctness of SAT solvers:

- All top-tier solvers emit proof logging (also for re-encoding)
- Formally-verified tools can efficiently certify the proofs

How to lift this success to richer logics (SMT/HWMC/FOL)?

# Conclusions and Challenges

We can have full confidence in the correctness of SAT solvers:

- All top-tier solvers emit proof logging (also for re-encoding)
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How to lift this success to richer logics (SMT/HWMC/FOL)?

Linear speedups are possible on a range of problems

- Even when using 1000s of CPUs;
- And the enormous proofs can be validated in parallel.

Various challenges:

- Make the techniques effective on a broader range of problems
- Expand the potential users: automated reasoning in the cloud
- Explainable automated reasoning to increase understanding

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