

# Learning Reductions with Descriptive Complexity and SAT Solvers

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July 26, 2013

# The Magic of SAT

**find**  $x$  : “ $x$  is good”

## Reduction Finding

**find**  $r$  :  $\forall x (x \in P \leftrightarrow r(x) \in Q)$

## Beyond SAT

**find**  $f$  :  $\forall x$  “ $f(x)$  is good”

### Questions

- How to represent  $r$ ,  $P$ ,  $Q$  and  $x$ ?
- How to approach the problem? **(CEGAR vs QBF vs ASP)**
- How do current tools perform?

# Motivation

## Finding Simple Objects

Often, we look for simple objects

- Gadgets, simpler formulas, reductions, counter-examples.

**Computers can help!**

## Related Work

- J., K. Experiments with Reduction Finding. SAT 2013.
- J., K. Benchmarks from Reduction Finding. QBF 2013.
- J., K. Learning Programs as Logical Queries. LTC 2013.
- Carmosino, Immerman, J. Experimental Descriptive Complexity. Kozen Festschrift, 2012.
- Itzhaky, Gulwani, Immerman, Sagiv. A simple inductive synthesis methodology and its applications. OOPSLA 2010.
- Crouch, Immerman, Moss. Finding Reductions Automatically. Gurevich Festschrift, 2010.

# Overview

## What is new?

- Unify work on synthesis and descriptive complexity
- Free, open reduction-finding tools
- Comparison of many approaches
- Benchmark instances

## Implementations

- ① <http://toss.sf.net/reduct.html>
- ② <http://toss.sf.net/reductGen.html>
- ③ <http://www-erato.ist.hokudai.ac.jp/~skip/de>
- ④ <http://toss.sf.net/gameGen.html>

Focus on *performance* of tools.

**How do we represent  
reductions?**

# Representing Reductions

**reduction**  $r : \forall x (x \in P \leftrightarrow r(x) \in Q)$

## Standard reductions

- $r$  is a (ptime, logspace, ...) **Turing machine**
- $x$  is a **word**
- $P, Q$  are sets of words given by **Turing machines**

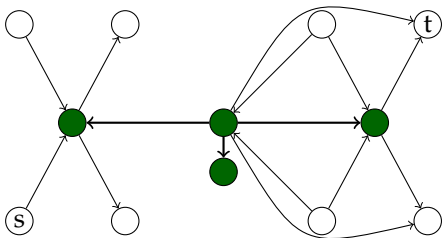
## Reductions in logic

- $r$  is a (quantifier-free, first-order, ...) **query**
- $x$  is a **relational structure**
- $P, Q$  are sets of structures given by **formulas**

**Question:** is there a useful correspondence?

# Relational Structures and Logics

**Relational Structures**  $A = (U, R_1^A, R_2^A, \dots, R_r^A, c_1^A, \dots, c_d^A)$



**First-Order and Second-Order Logic** over  $\sigma = \{E\}$

Clique (FO):  $\forall x, y: (x = y \vee E(x, y))$

3-colorable ( $\exists$ SO):

$\exists R, G, B \forall x, y: (R(x) \vee G(x) \vee B(x)) \wedge$   
 $(E(x, y) \rightarrow \neg ((R(x) \wedge R(y)) \vee (G(x) \wedge G(y)) \vee (B(x) \wedge B(y))))$

# Descriptive Complexity

Decision problem  $P$

**Computational complexity:** resources needed to check it

**Descriptive complexity:** **expressive power** needed to define it

The two notions are **isomorphic!**

“Hard to check”  $\equiv$  “Requires expressive language to define”

## Characterizations of complexity classes

- PSPACE = SO(TC)
- NP = SO $\exists$ , coNP = SO $\forall$ , PH = SO
- P = FO(LFP)
- NL = FO(TC) . . .



# Queries

**Queries (Interpretations)**  $q = (k, \varphi_0, \varphi_1, \dots, \varphi_r, \psi_1, \dots, \psi_d)$

- $k$  is the dimension
- $\varphi_0(x_1, \dots, x_k)$  defines the new universe
- $\varphi_i(x_1, \dots, x_{ka_i})$  define the new relations
- $\psi_j(x_1, \dots, x_k)$  define the new constants

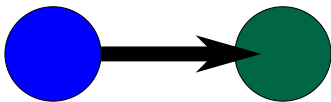
## Example

(  $k = 2, \varphi_0 = \top, \varphi(x_1, x_2, x_3, x_4) = (x_1 = x_3) \wedge E(x_2, x_4)$  )

**Choice of logic**  $\equiv$  **Complexity of query**

# Reductions

**reduction**  $r : \forall x (x \in P \leftrightarrow r(x) \in Q)$



## Weak Reductions Suffice!

Quantifier-free projections suffice for natural problems.  
No need to prove things can't be done in **polytime**<sup>1</sup>.

**Example:** <http://toss.sf.net/reduct.html>

## Same Example:

$q := \langle k := 1, \varphi_0 := \top, \varphi_1(x_1, x_2) := x_1 = s \vee x_2 = t \vee E(x_2, x_1) \rangle$

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<sup>1</sup>E.g., Berman-Hartmanis conjecture *holds* for first-order projections!

# Decidability and Parameters

$$\exists r : \forall x : (x \in P \leftrightarrow r(x) \in Q)$$

**But this formula is infinite!**

## Decidability via Parameters:

$k$  dimension of the reduction

$n$  size of examples ( $x$ )

$c$  number of conjunctions in DNF

**The formula is finite!**

In spirit, a  $\Sigma_2^P$  problem.

# How to approach the problem?

## CEGAR vs QBF vs ASP

# Approaches to $\Sigma_2^P$

## Quantified Boolean Formula (QBF) Solvers

- PSPACE-complete, one call suffices
- CNF-conversion, prenexing: *problematic*
- 3QBF CNF, 2QBF CNF (negated), qpro (NNF), CQBF (experimental)

## Disjunctive Answer Set Program (ASP) Solvers

- Disjunctive  $\equiv \Sigma_2^P$ , one call suffices
- Faber, Ricca. Solving hard ASP programs efficiently NMR 2005.
- **Few solvers**: claspD, cmodels, gnt(2)

## Counter-example guided abstraction refinement (CEGAR)

- Crouch, Immerman, Moss. Finding reductions automatically. Gurevich Festschrift, 2010.
- Janota, Marques-Silva. Abstraction-based algorithm for 2QBF. SAT 2011.
- Janota, Klieber, Marques-Silva, Clarke. Solving QBF with counterexample guided refinement. SAT 2012.

# CEGAR, SAT and $\Sigma_2^P$

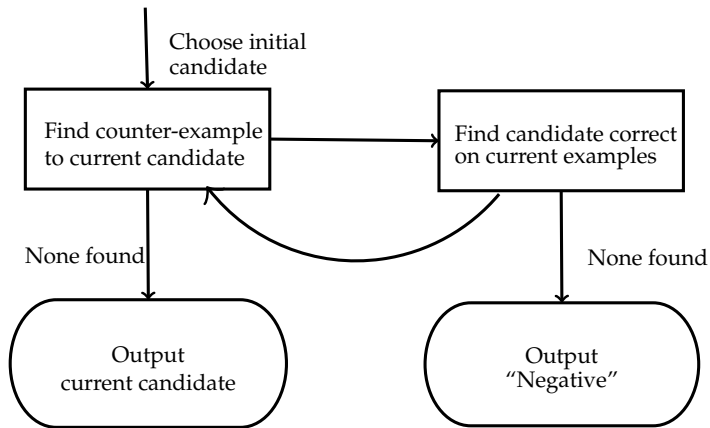


Figure: Counter-example guided abstraction refinement (CEGAR)

**How do current tools perform?**

# Compared

## Instances

2304 instances per parameter set, 6+ sets, plus hard instances

## DE (incremental)<sup>2</sup>

MiniSat-2<sup>3</sup>, GlueMiniSat, CryptoMiniSat, BDD/CUDD

## Toss (not incremental)

MiniSat-2, GlueMiniSat, Intel Decision Procedure Toolkit

## QBF (qdimacs+nqdimacs)

rareqs, depqbf, QuBE, sKizzo, CirQit (qpro too)

## ASP

(lparse, gringo) × (gnt2, cmodels, claspd)

## Reduction Finder

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<sup>2</sup>Preliminary runs with lingeling, treengeling, plingeling, PMSat, ...

<sup>3</sup>No simplification – <https://github.com/niklasso/minisat/issues/3>



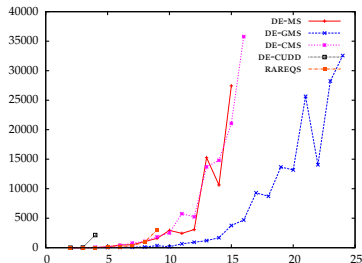
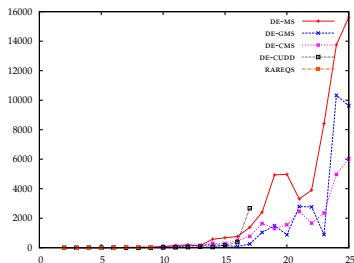
# Reduction Finding Results

# Unsolved cases of  $48 \times 48 = 2304$ : **CEGAR** vs **QBF** vs **claspD**

$(c, n)$	(1, 3)	(2, 3)	(3, 3)	(1, 4)	(2, 4)	(3, 4)
DE-GMS	0	0	10	0	5	103
DE-CUDD	0	116	537	0	186	722
RAREQS	0	0	16	19	65	204
DEPQBF	0	142	547	16	297	711
QUBE	10	536	949	82	760	1082
CIRQIT	58	673	1138	511	1092	1357
CIRQIT'	157	523	903	–	–	–
SKIZZO	522	1058	1156	975	1327	1434
GRINGO	40	393	590	72	593	836
LPARSE	51	396	605	75	635	850
RedFind	1	152	396	2	347	547

# CEGAR Results

REACH to REACH,  $k = 1$ , scaling  $n$  with  $c = 1, 2$



**Dimension 2** ( $c = 1$ )

	DE-MS	DE-GMS	DE-CMS	DE-CUDD	RAREQS
$k = 1, n = 3$	0.05	0.06	0.08	0.07	0.03
$k = 2, n = 2$	0.06	0.11	0.28	6.30	0.06
$k = 2, n = 3$	3562.14	1696.26	1755.03	timeout	3267.10

# QBF Gallery 2013 (Lonsing, Seidl, van Gelder)

14 QBF solvers on random sample of  $k = 1, c = 3, n = 4$ .

# of instances (of 150) solved in 900s.

<http://www.kr.tuwien.ac.at/events/qbfgallery2013/>

# Outlook

## What can we do?

- Simple evaluation and reduction finding
- <http://www-erato.ist.hokudai.ac.jp/~skip/de>
- <http://toss.sf.net/reduct.html>
- Useful as a *debugger*!
- Source of uniform instances. parameters  $\rightarrow$  hardness

## What is hard?

- high-dimensional reductions
- symmetry breaking in example finding problems
- using GPUs, massively parallel machines

# Related Future Work

## Finding Fast Programs

- Learn LFP equivalents to SO
- **Examples:** parity games, graph isomorphism, SAT
- **LFPTest.native**

## Solving Games

- Does Player 1 win?
- <http://toss.sf.net/gameGen.html>
- **Note:** CEGAR loses to other solvers!

## Learning Games

- Given set of example plays, learn rules
- **Examples:** Connect4, gomoku, chess
- J.,K. Learning Programs as Logical Queries, LTC 2013.

## Much More!

# Reason to Hope

## **Ranges**

Start with size-2 examples, then move to 3. . .

*Very big* performance gain. Not enough for  $k = 3$ .

## **Encodings & More**

QBF/SAT 2013 were inspiring – much to do!

## **Parallel & supercomputing**

Cube and conquer? (march, treengeling, . . .)

## **Benchmarks**

New QBF benchmarks, new QBF formats, ASP/etc.  
benchmarks in progress

## **New Ideas and Approaches?**

We're new!

Thank you!

