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Joint work with

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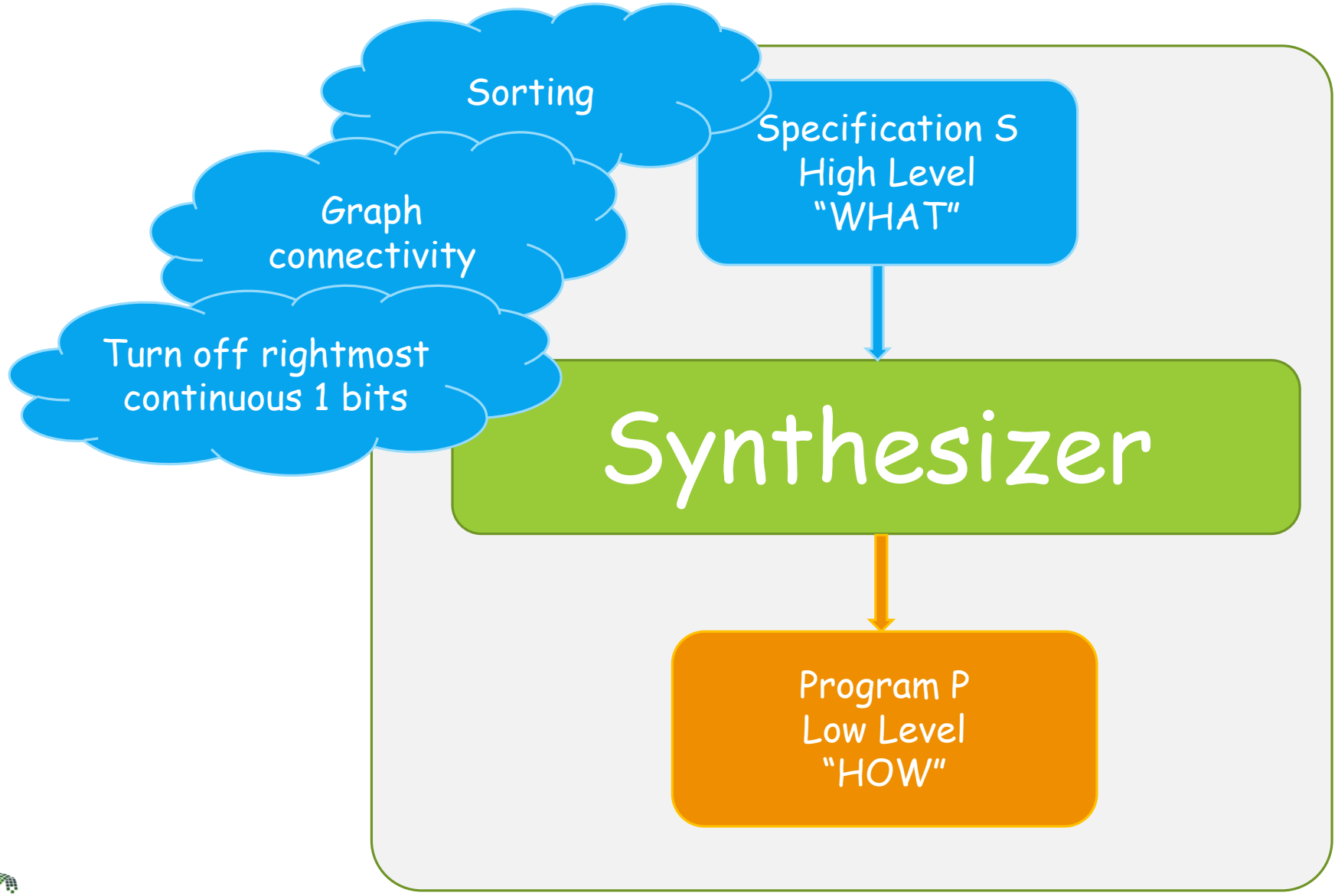
Syntax-Guided Synthesis

Talk Outline

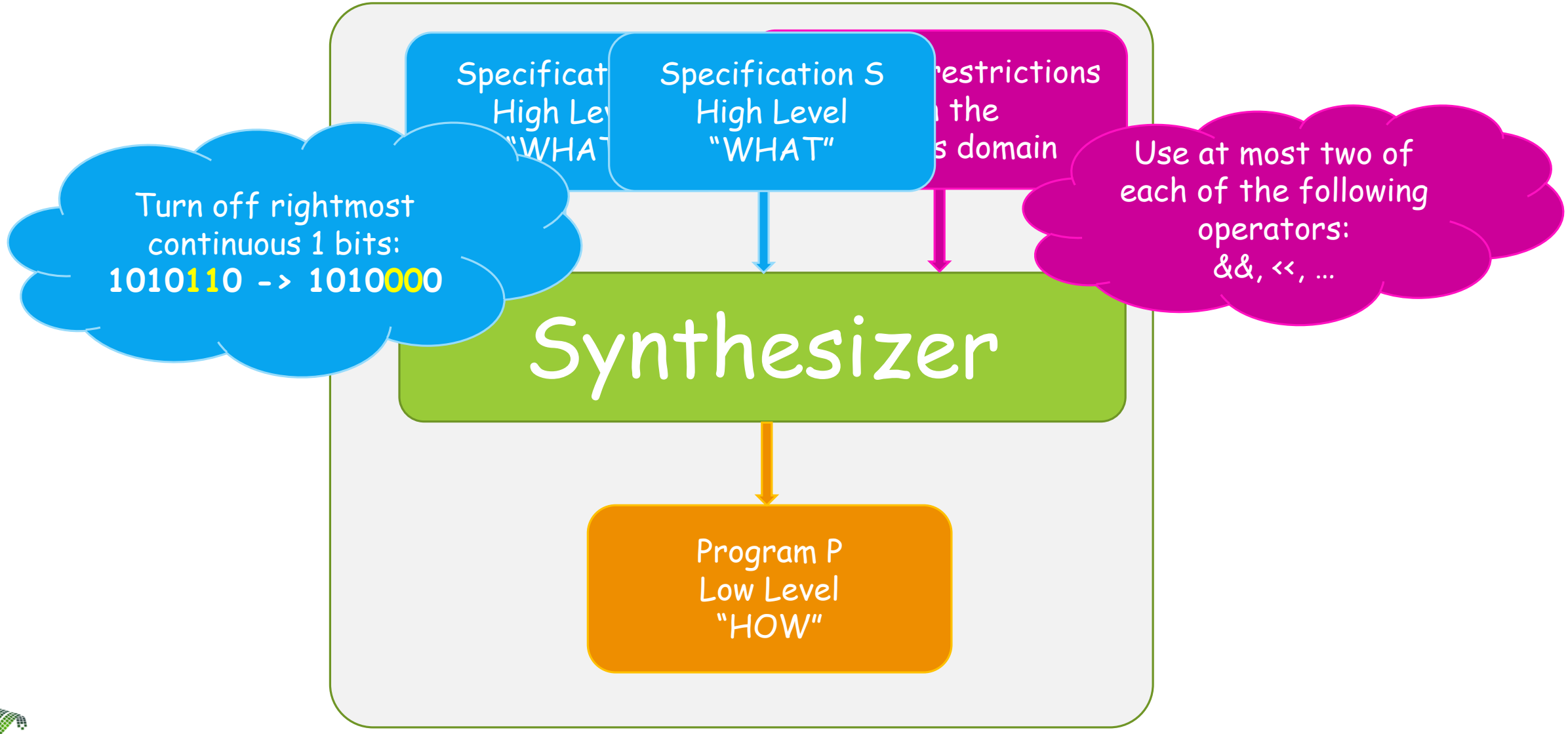
- Motivation for Syntax-Guided Synthesis
  - Recent trends in program synthesis (the problem)
  - The big picture, SAT & SMT success stories (the inspiration)
- Formalization of Syntax-Guided Synthesis
- Solution Strategies
- SyGuS Competition Results

SyGuS

Program Synthesis



New Trends in Synthesis



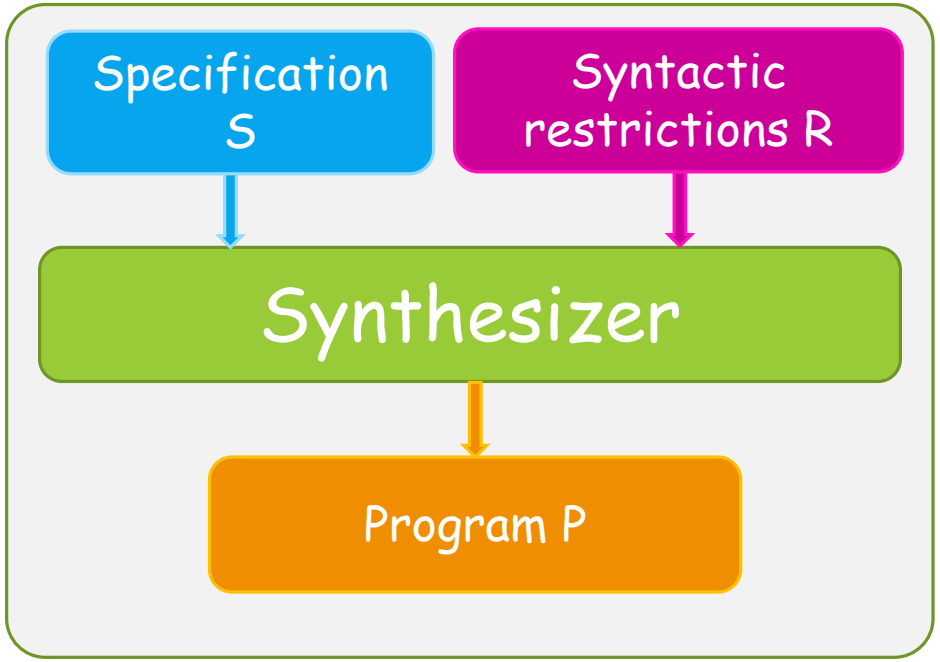
New Trends in Synthesis

Motivation:

- Tractability
- Combine

  human expert insights with

  computers exhaustiveness & rapidness
- Benefit progress SAT & SMT Solvers



SyGuS

Ex 1. Parallel Parking By Sketching

The challenge is finding the parameters

When to start turning?

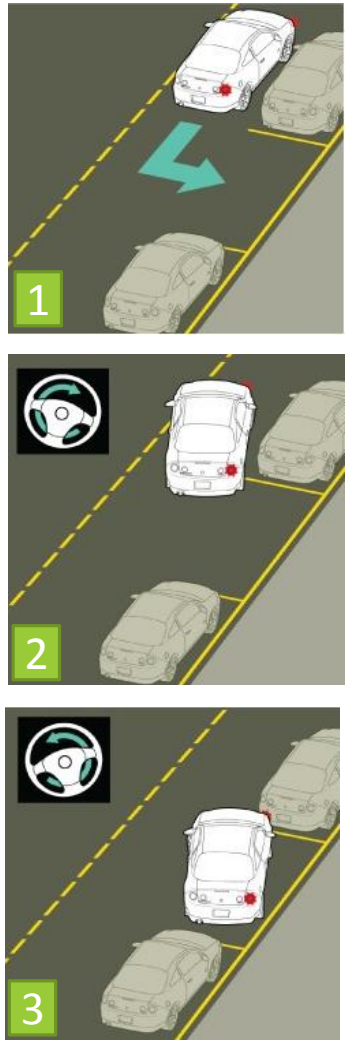
How much to turn?

```
Err = 0.0;
for(t = 0; t<T; t+=dT){
  if(stage==STRAIGHT){ // (1) Backup straight
    if(t > ??) stage= INTURN;
  }

  if(stage==INTURN){ // (2) Turn
    car.ang = car.ang - ??;
    if(t > ??) stage= OUTTURN;
  }

  if(stage==OUTTURN){ // (3) Straighten
    car.ang = car.ang + ??;
    if(t > ??) break;
  }

  simulate_car(car);
  Err += check_collision(car);
}
Err += check_destination(car);
```



Structure of the program is known

[Chaudhuri & Solar-Lezama PLDI 2010]

SyGuS

Ex 2. Optimizing Multiplications

Superoptimizing Compiler

Given a program P, find a "better" equivalent program P'.

```
multiply (x[1,n], y[1,n]) {
    x1 = x[1,n/2];
    x2 = x[n/2+1, n];
    y1 = y[1, n/2];
    y2 = y[n/2+1, n];
    a = x1 * y1;
    b = shift( x1 * y2, n/2);
    c = shift( x2 * y1, n/2);
    d = shift( x2 * y2, n);
    return ( a + b + c + d)
}
```

Replace with equivalent code with only 3 multiplications

SyGuS

Ex 3. Automatic Invariant Generation

Given a program P and a post condition S,

Find invariants I_1, I_2 with which we can prove program is correct

```
SelecionSort(int A[],n) {
  i1 :=0;
  while(i1 < n-1) {
    v1 := i1;
    i2 := i1 + 1;
    while (i2 < n) {
      if (A[i2]<A[v1])
        v1 := i2 ;
      i2++;
    }
    swap(A[i1], A[v1]);
    i1++;
  }
  return A;
}
```

Invariant: ???

Invariant: ???

post: $\forall k : 0 \leq k < n \Rightarrow A[k] \leq A[k+1]$

SyGuS

Ex 3. Template-Based Invariant Generation

Given a program P and a post condition S

Find invariants I_1, I_2, … I_k with which we can prove program is correct

```
SelecionSort(int A[],n) {
  i1 :=0;
  while(i1 < n-1) {
    v1 := i1;
    i2 := i1 + 1;
    while (i2 < n) {
      if (A[i2]<A[v1])
        v1 := i2 ;
      i2++;
    }
    swap(A[i1], A[v1]);
    i1++;
  }
  return A;
}
```

Invariant:
∀k1,k2. ??? ∧ ???

Invariant:
??? ∧ ??? ∧
(∀k1,k2. ??? ∧ ???) ∧
(∀k. ??? ∧ ?)

Constraint Solver

post: ∀k : 0 ≤ k <n ⇒ A[k] ≤ A[k+1]

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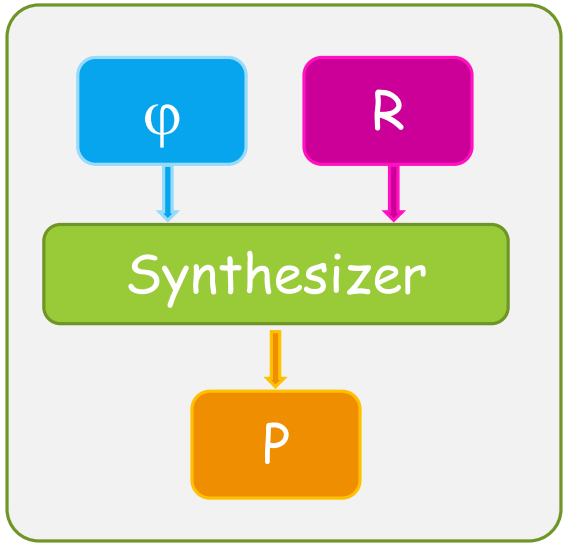
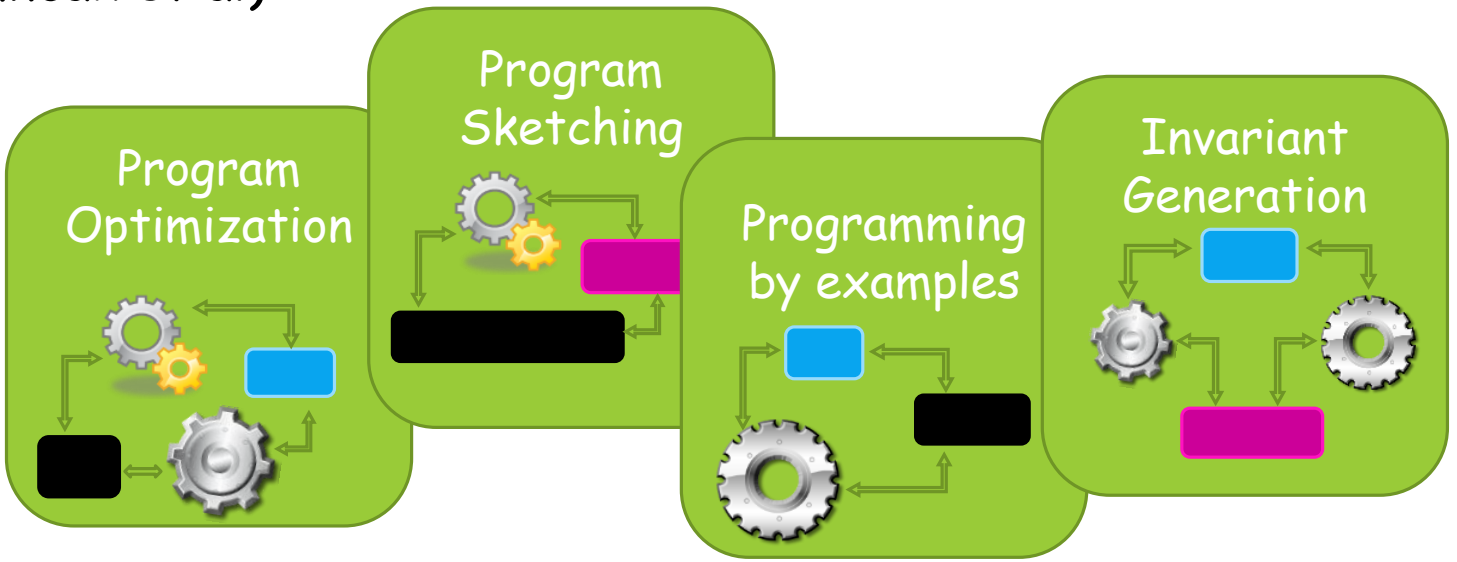
Syntax-Guided Program Synthesis

- Common theme to many recent efforts
  - Sketch (Bodik, Solar-Lezama et al)
  - FlashFill (Gulwani et al)
  - Super-optimization (Schkufza et al)
  - Invariant generation (Many recent efforts…)
  - TRANSIT for protocol synthesis (Udupa et al)
  - Oracle-guided program synthesis (Jha et al)
  - Implicit programming: Scala^Z3 (Kuncak et al)
  - Auto-grader (Singh et al)



But no way to have
a generic solver for all ☹



SyGuS

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Slide adapted from a presentation of Viktor Kuncak

The Big Picture

Given list i
is P(i) sorted?

Does prog P
always sorts
correctly?

Given
Prog P
Spec S

Assertion Checking:

overall correctness / partial/ intermediate

P(i) |= S(i) ?

Program Verification:

∀i: P(i) |= S(i) ?

Given
only
Spec S

Constraint Programming:

Find o: o |= S(i)

Program Synthesis:

Find P: ∀i: P(i) |= S(i)

Given list i,
return it sorted

...ntime

Cor...

Return a sorting
program P

SyGuS

The Big Picture

Given
Prog P
Spec S

Assertion Checking:

$P(i) \models S(i)$?

Program Verification:

$\forall i: \quad P(i) \models S(i)$?

Given
only
Spec S

Return a program P
implementing turnoff
rightmost 1's

Program Synthesis:

$\exists P: \quad \forall i: P(i) \models S(i)$

Return a program P
implementing turnoff
rightmost 1's using only
so and so operators

Syntax-Guided Synthesis:

$\exists P \in [\![R]\!]: \quad \forall i: P(i) \models S(i)$

SyGuS

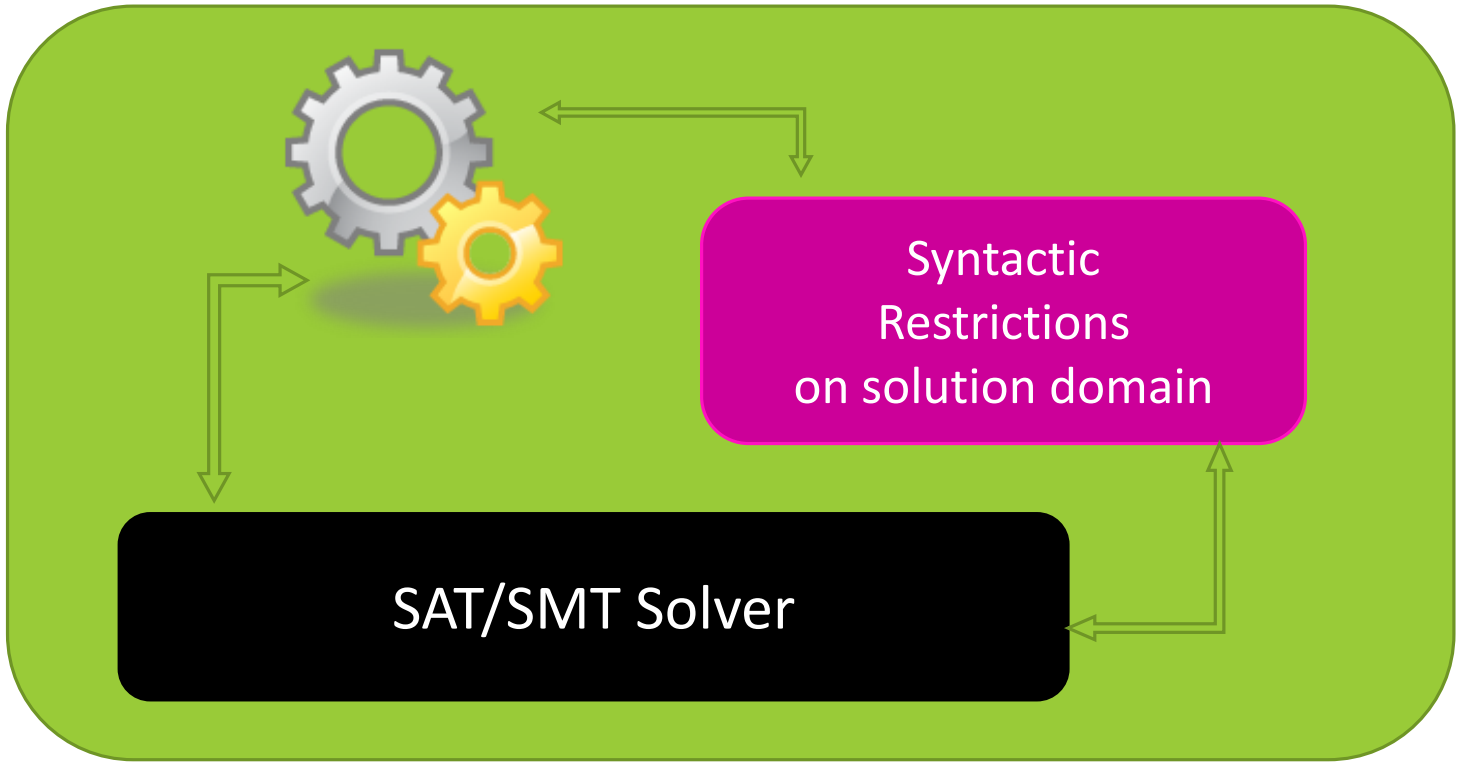
From Satisfiability to Synthesis

Recent trends in program synthesis:

P(i) |= S(i) ?	∀i: P(i) |= S(i) ?
∃o: o |= S(i)	∃P: ∀i: P(i) |= S(i)
	∃P∈⟦R⟧: ∀i: P(i) |= S(i)

Problem

(verif/synth nature)



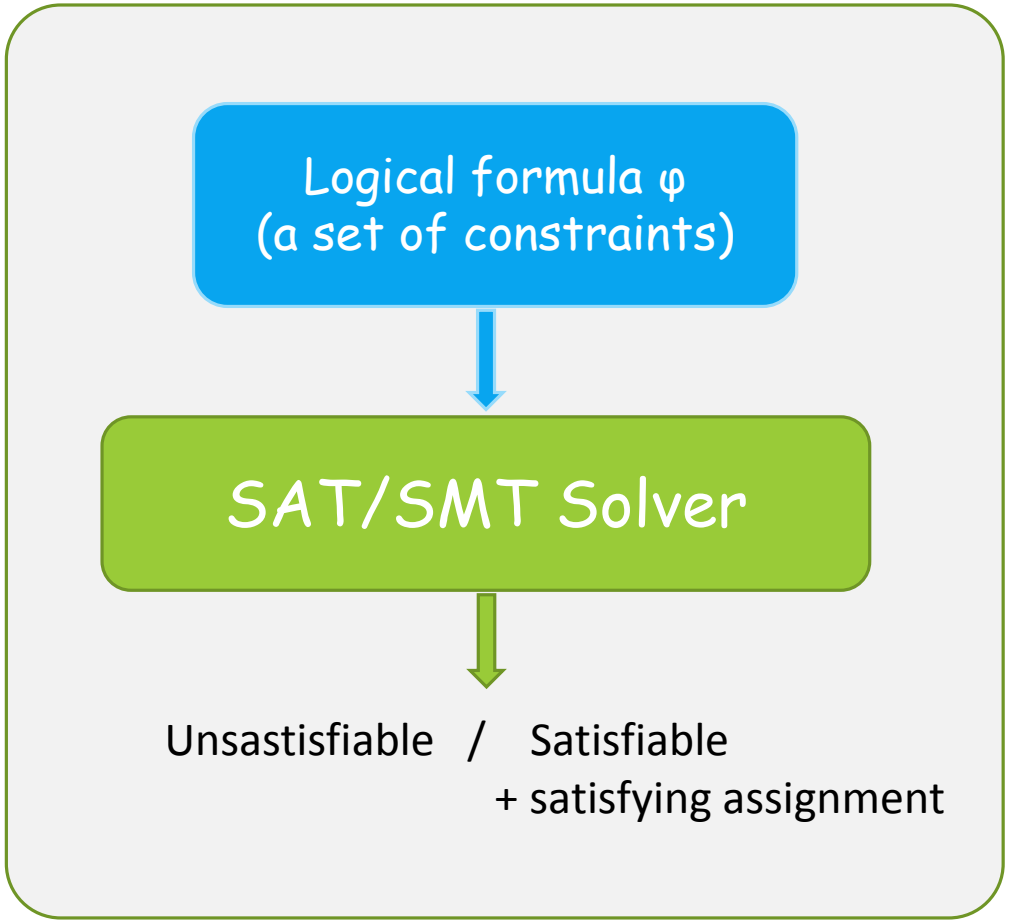
SAT and SMT Solvers

Satisfiability

Is formula φ, satisfiable?

- SAT
  Formulas use Boolean variables + Logical connectives

- SMT
  (Satisfiability ModuloTheories)
  Formulas are interpreted in some theory, e.g. BitVectors, Integers, Unintepreted functions.



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SAT & SMT Solvers and Verification Tools

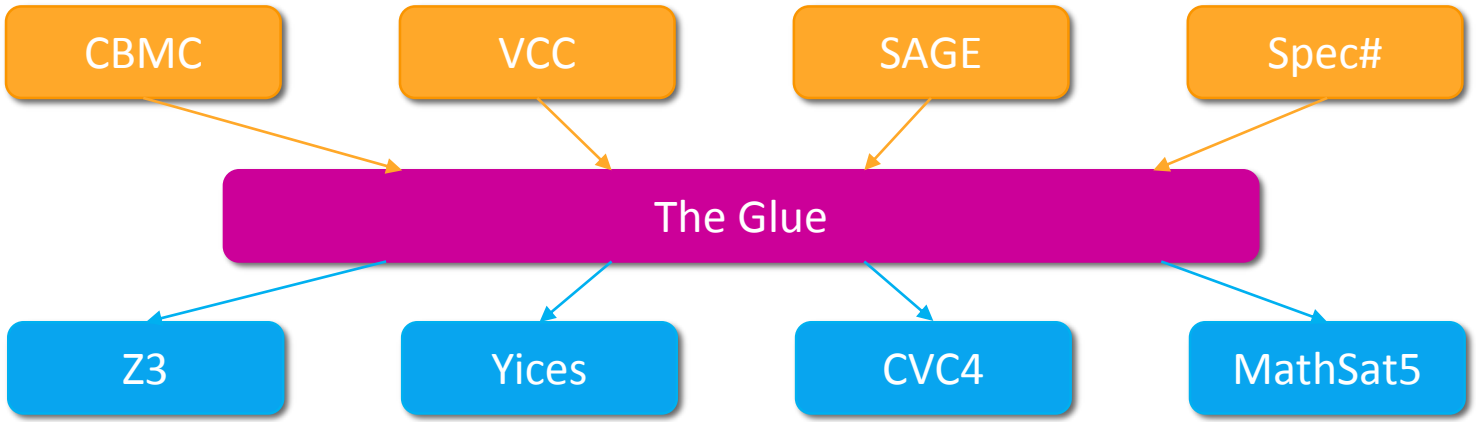
- Fundamental Thm of CS:

  SAT is NP-complete (Cook, 1971)

- Nonetheless, todays' SAT solvers are capable of handling instances with 20K variables.
- Continuous progress in SMT solvers achieved among other things via

The Glue:
- SMT-LIB standardization
- currently over 100,000 benchamrks
- annual competition

- Many verification tools build on SMT solvers



SyGuS

SyGuS - The Vision

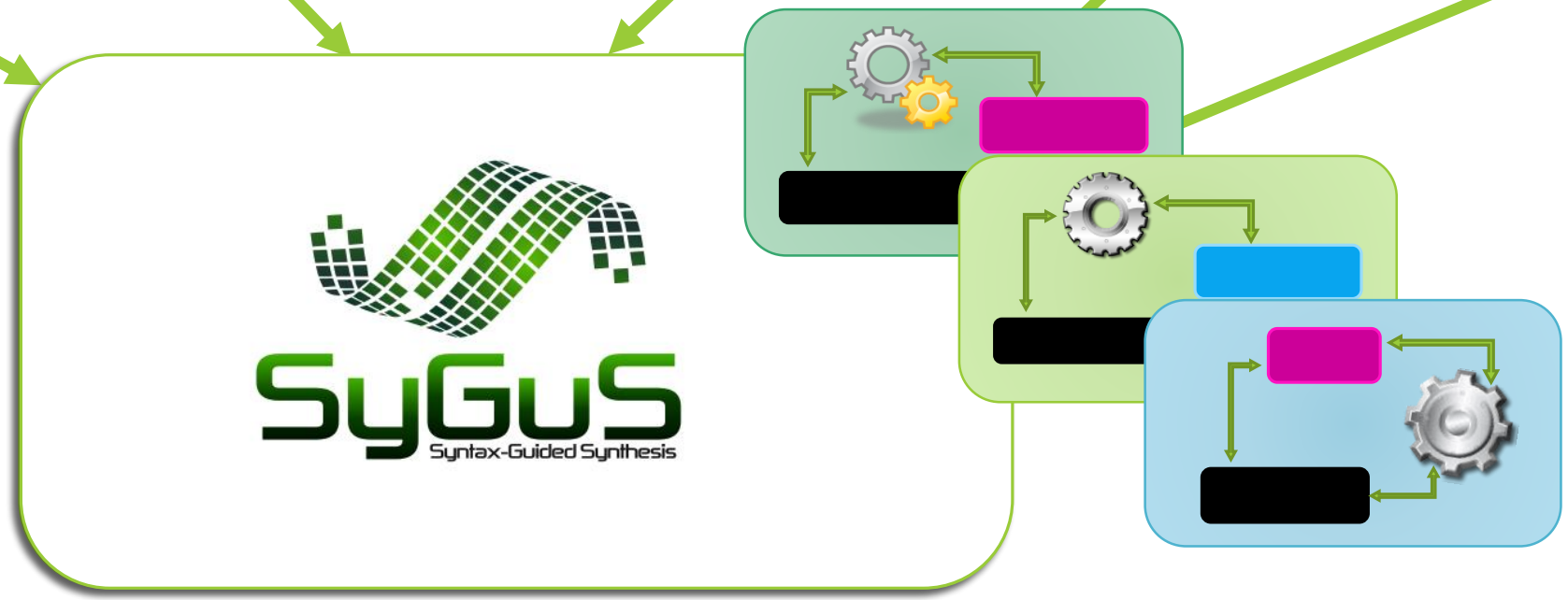
Program Optimization

Program Sketching

Programming by examples

Invariant Generation

?????



Talk Outline

- Motivation for Syntax-Guided Synthesis
  - Recent trends in program synthesis (the problem)
  - The big picture, SAT & SMT success stories (the inspiration)
- **Formalization of Syntax-Guided Synthesis**
- Solution Strategies
- SyGuS Competition Results

SyGuS

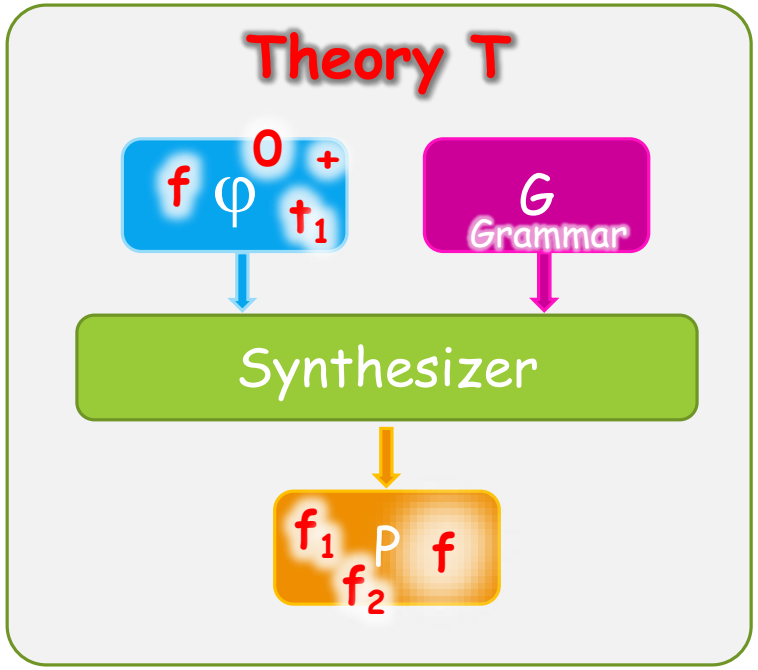
Syntax-Guided Synthesis (SyGuS) Problem

- Fix a background theory T: fixes types and operations
- Function to be synthesized: name f along with its type
  - General case: multiple functions to be synthesized
- Inputs to SyGuS problem:
  - Specification φ

    Typed formula using symbols in T + symbol f
  - Context-free grammar G

    Characterizing the set of allowed expressions ⟦G⟧ (in theory T)
- Computational problem:

  Find expression e in ⟦G⟧ such that φ[f/e] is valid (in theory T)



SyGuS

SyGuS – formalization example

- Theory QF-LIA
  Types: Integers and Booleans
  Logical connectives, Conditionals, and Linear arithmetic
  Quantifier-free formulas

- Function to be synthesized f (int x, int y) : int

- Specification: $f(x,y) \geq x$ &
  $f(x,y) \geq y$ &
  ($f(x,y)=x$ | $f(x,y)=y$)

- Candidate Implementations: Linear expressions

  LinExp := x | y | Const | LinExp + LinExp | LinExp - LinExp

- No solution exists

SyGuS - formalization example

- Theory QF-LIA
  Types: Integers and Booleans
  Logical connectives, Conditionals, and Linear arithmetic
  Quantifier-free formulas

- Function to be synthesized f (int x, int y) : int

- Specification: $f(x,y) \geq x$ &
  $f(x,y) \geq y$ &
  ($f(x,y)=x$ | $f(x,y)=y$)

- Candidate Implementations: Conditional expressions with comparisons

  Term := x | y | Const | If-Then-Else (Cond, Term, Term)
  Cond := Term $\leqslant$ Term | Cond & Cond | ~Cond | (Cond)

- Possible solution:
  If-Then-Else ($x \leq y$, y, x)

SyGuS

Let Expressions

- Synthesized expression maps directly to a straight-line program
- Grammar derivations correspond to expression parse-trees
- Problem:
  How to capture common sub-expressions (which map to aux vars) ?
- Solution:
  Allow "let" expressions
- Candidate-expressions for a function f(int x, int y) : int

```
U  :=  x | y | Const | (U) | U + U | U*U |
       (let ((z int U)) in  U)
```

SyGuS

Talk Outline

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SyGuS

Solving SyGuS

P(i) |= S(i) ?

∀i: P(i) |= S(i) ?

∃o: o |= S(i)

∃P: ∀i: P(i) |= S(i)

∃P∈⟦G⟧: ∀i: P(i)|= S(i)

- Is SyGuS same as solving SMT formulas with quantifier alternation?

$$\exists P \in [\![G]\!]: \forall i: P(i) \models S(i)$$

- SyGuS can sometimes be reduced to Quantified-SMT, but not always
  - Set ⟦G⟧ is all linear expressions over input vars x, y

    SyGuS reduces to ∃a,b,c. ∀x,y. φ [f / ax+by+c]
  - Set ⟦G⟧ is all conditional expressions

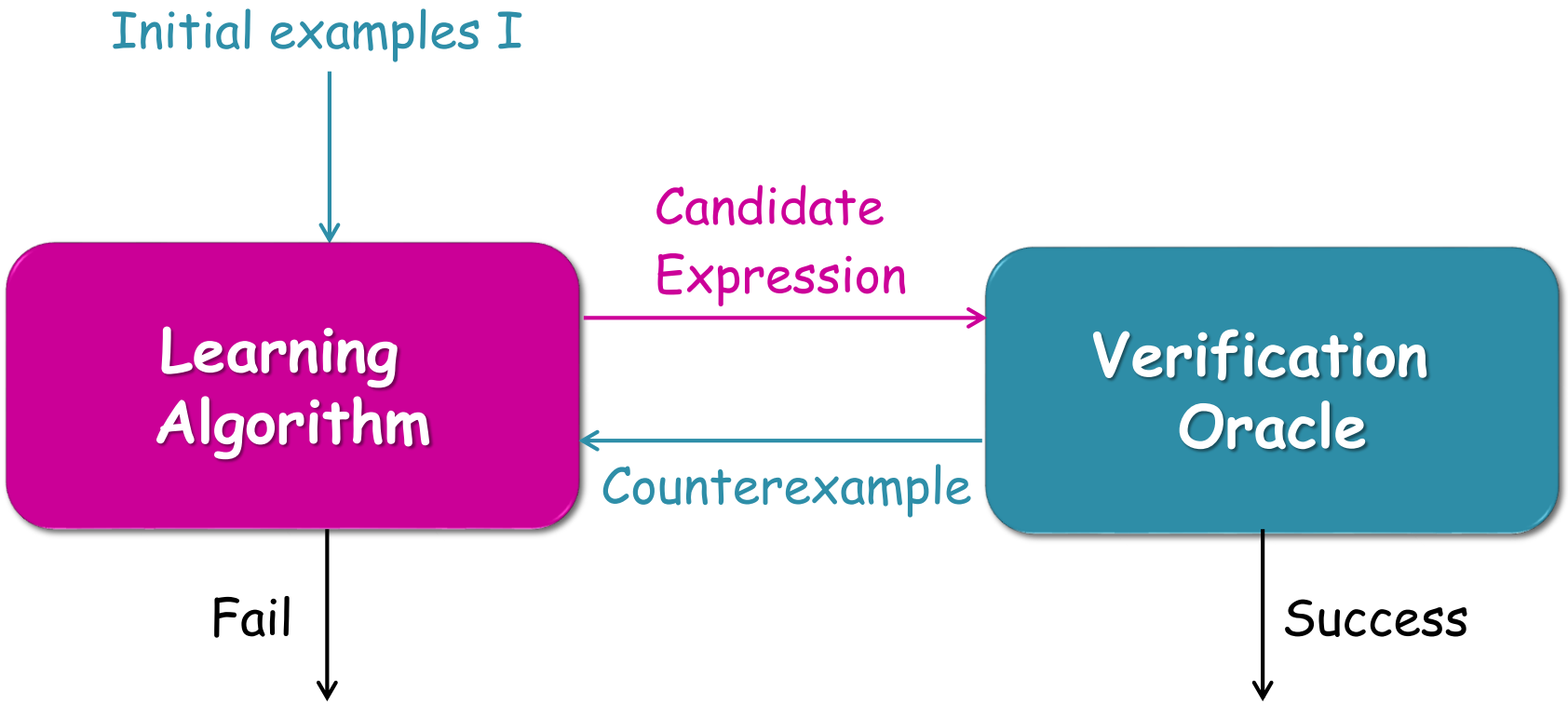
    SyGuS cannot be reduced to deciding a formula in LIA

- Syntactic structure of the set ⟦G⟧ of candidate implementations can be used effectively by a solver

- Existing work on solving Quantified-SMT formulas suggests solution strategies for SyGuS

SyGuS

SyGuS as Active Learning



Concept class: Set ⟦G⟧ of expressions

Examples: Concrete input values

Running Example

- Specification:

$$(x \leq f(x,y)) \;\&$$
$$(y \leq f(x,y)) \;\&$$
$$(f(x,y) = x \mid f(x,y) = y)$$

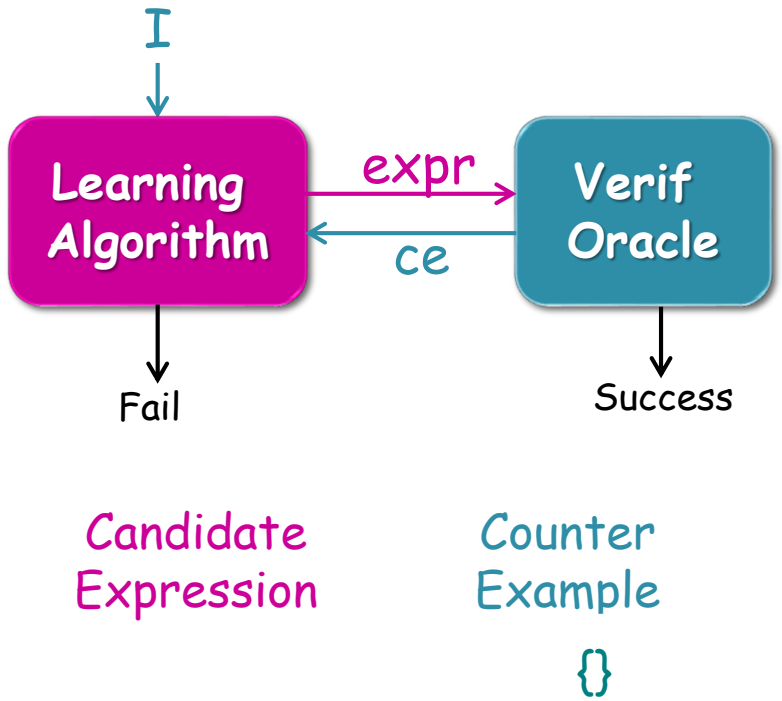
- Syntactic Restrictions:

all expressions built from x,y,0,1,
<=, =, =>, +,
If-Then-Else

SyGuS

SyGuS as Active Learning (CEGIS)

- Concrete inputs I for learning
  $f(x,y) = \{ (x=a_0,y=b_0),\ (x=a_1,y=b_1), \ldots.\}$
- Learning algorithm proposes candidate expression e such that $\varphi[f/e]$ holds for all values in I
- Check if $\varphi[f/e]$ is valid for all values using SMT solver
- If valid, then stop and return e
- If not, let (x=a, y=b, ….) be a counter-example (satisfies ~ $\varphi[f/e]$)
- Add (x=a, y=b) to tests I for next iteration



SyGuS Solutions

- CEGIS - Counter-Example Guided Inductive Synthesis approach (Solar-Lezama, Seshia et al)

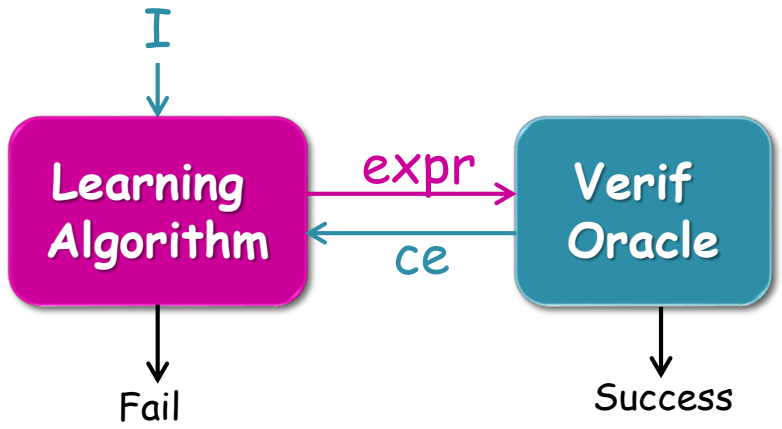
- Related work: Similar strategies for solving quantified formulas and invariant generation

- Learning strategies based on:
  - Enumerative (search with pruning): Udupa et al (PLDI'13)
  - Symbolic (solving constraints): Library components - Gulwani et al (PLDI'11);
    Sketch-based – Solar-Lezama et al (PhD thesis, UCB, 2008)
  - Stochastic (probabilistic walk): Schkufza et al (ASPLOS'13)
  - Geometric (learns guarded linear expressions): Garg et al.

SyGuS

Enumerative

- Find an expression consistent with a given set of concrete examples
- Enumerate expressions in increasing size, and evaluate each expression on all concrete inputs to check consistency
- Key optimization for efficient pruning of search space:
  - Expressions e_1 and e_2 are equivalent if $e_1(a,b)=e_2(a,b)$ on all concrete values (x=a,y=b) in Examples
  - E.g. If-Then-Else ($0 \le x, e_1, e_2$) considered equivalent to e_1 if in current set of Examples x has only non-negative values
  - Only one representative among equivalent sub-expressions needs to be considered for building larger expressions



SyGuS

Symbolic CEGIS

- Recall, in general we cannot use SMT solvers to solve SyGuS

$$\exists P \in [\![G]\!] : \forall i : P(i) \models S(i)$$

- Idea:

  We can use the constraint solver also in the learning algorithm by restricting the size/depth of the expressions

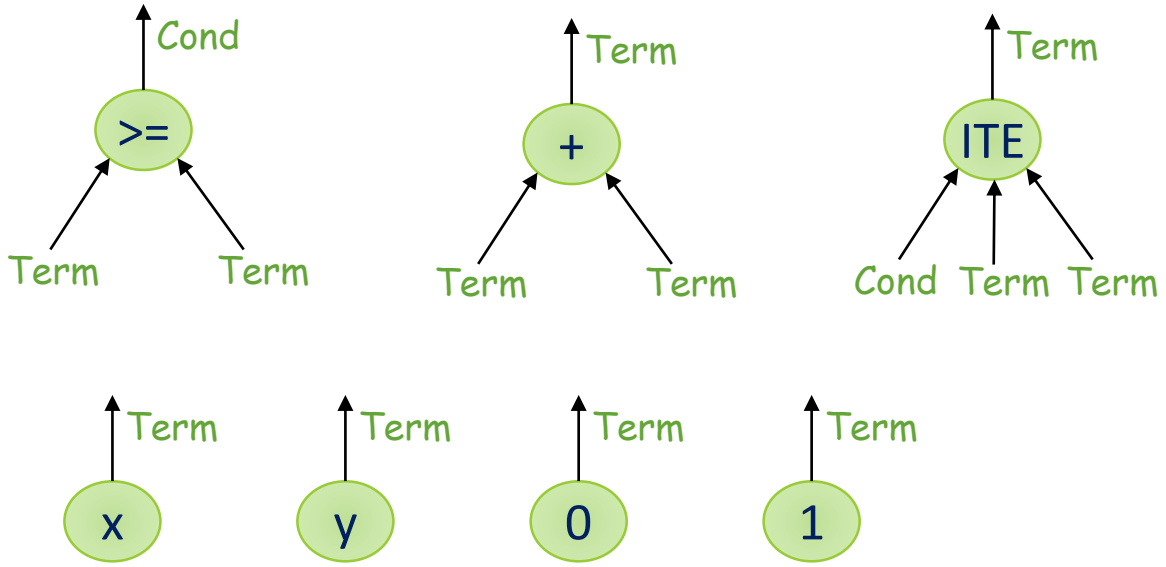
- We need a way to encode the restricted set of expressions, and if no such expression exists, increase the size

- Two versions:
  - Symbolic [Jha et al.]
  - Sketch-Based [Solar-Lezama et al.]

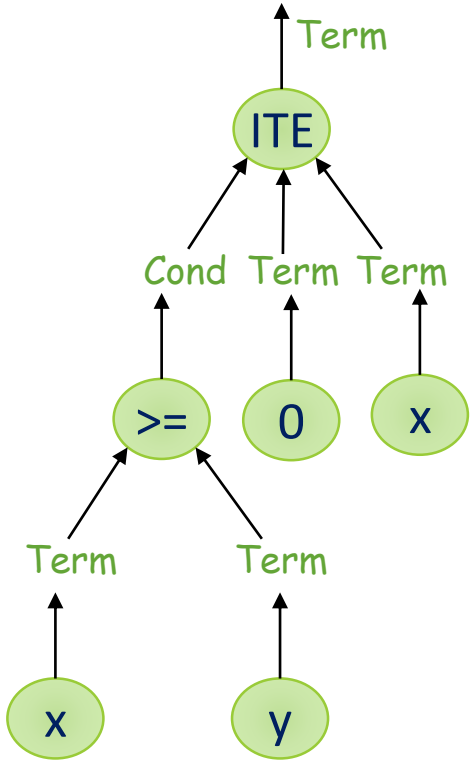
SyGuS

Symbolic [Jha et al.]

- Each production in the grammar is though of as a library component



- A well-typed loop-free program comprising these component corresponds to an expression DAG from the grammar



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Symbolic [Jha et al.]

- Start with a library consisting of some number of occurrences of each component.

- Synthesis Constraints:
  - Program composed of library's component, Shape is a DAG, Types are consistent
  - Spec $\varphi[f/e]$ is satisfied on every concrete input values in Examples

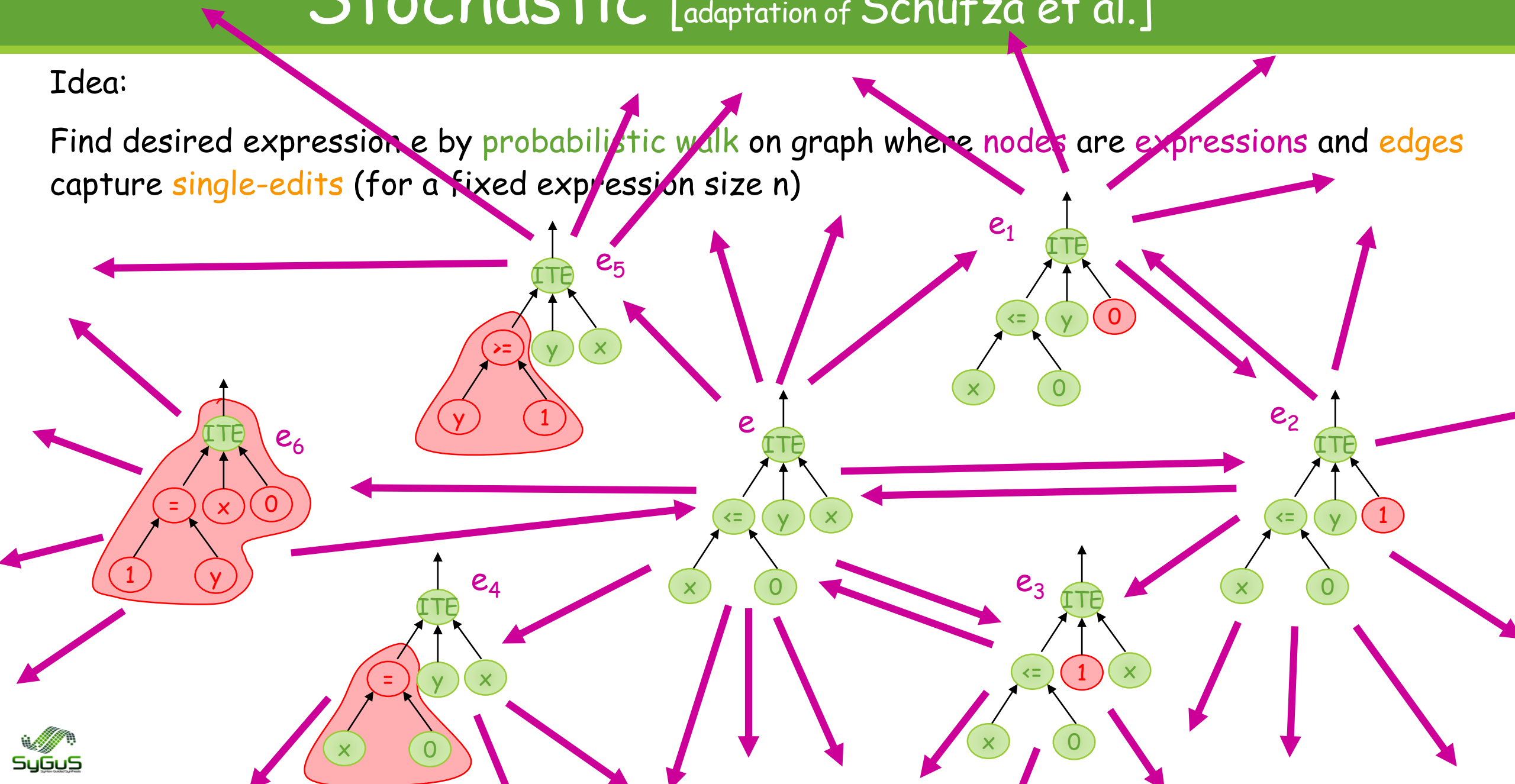
- Use an SMT solver to find a satisfying solution.
  - If synthesis fails, try increasing the number of occurrences of components in the library in an outer loop.

SyGuS

Stochastic [adaptation of Schufza et al.]

Idea:

Find desired expression e by probabilistic walk on graph where nodes are expressions and edges capture single-edits (for a fixed expression size n)



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Stochastic

- Metropolis-Hastings Algorithm: Given a probability distribution P over domain X, and an ergodic Markov chain over X, samples from X
- Because the graph is strongly connected, we can reach each node with some probability
- Let Score(e) be the "Extent to which e meets the spec φ"
  Having $P(e) \propto Score(e)$ we increase the chances of getting to expressions with better score.
  To escape "local minima" we allow with some probability moving to expressions with lower score.
- Specific choice of score:
  For a given set I of concrete inputs, $Score(e) = \exp(-\frac{1}{2} Wrong(e))$
  where Wrong(e) = No of examples in I for which $\sim \varphi [f/e]$
- Score(e) is large when Wrong(e) is small
  => Expressions e with Wrong(e) = 0 more likely to be chosen in the limit than any other expr

SyGuS

Stochastic

- Initial candidate expression e sampled uniformly from E_n

- When Score(e) = 1, return e

- Pick node v in parse tree of e uniformly at random.

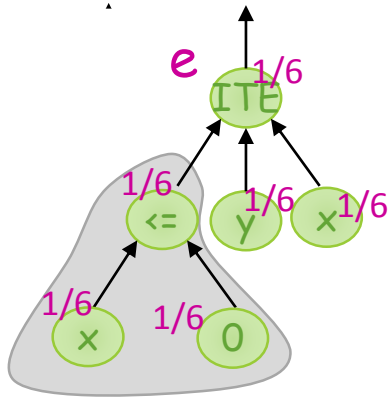
  Replace subtree rooted at v with subtree of same size, sampled uniformly

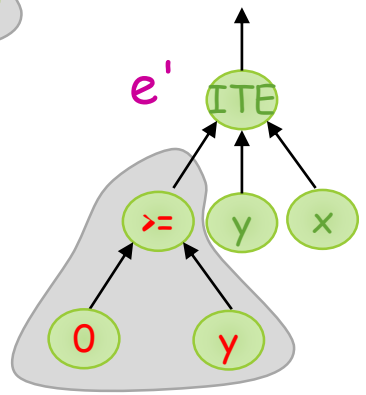
- With probability min{ 1, Score(e')/Score(e) }, replace e with e'

- Outer loop responsible for updating expression size n

SyGuS

- Expr size = 6
- All expressions of this size have the following form
- One chosen at random, with probability $1/(4\times4\times4\times4\times3) = 1/768$
- Suppose it is e = ITE(x <= 0, y, x)
- Next a sub-expression (node) to mutate is chosen at random
- Probability to mutate node 2 is 1/6
- There are $1/(4\times4\times3) = 1/48$ conditional expression node 2 can be replaced with
- Choice e' = ITE(0 <= y, y, x) is considered with probability $1/(48\times6) = 1/288$
- If concrete examples are (-1 , 4) (-3 , -1) (-1 , -2) (1 , 2) (3, 1) (6, 2)





- With |

Geometric

- Idea: Learns only guarded linear expression
  - Agnostic to the SyGuS constraints
  - Learns only from the examples
  - Examples are assumed to be given as (x, val) where x is a vector $(x_1, x_2, \ldots, x_k)$ of variables

Does not work for partially-specified problems, or problems which can not be implemented by guarded linear expressions or the grammar disallows it.

- Process:

Phase 1 [Geometry]:

- Synthesizes linear expressions $LE_1, LE_2, \ldots LE_k$, such that each example is evaluated correctly by at least one.
- Essentially finds a small set of planes that includes all given examples

Phase 2 [Classifier]:

- Synthesizes the guards using a fast and scalable machine learning algorithm for decision trees

SyGuS

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SyGuS

SyGuS Competition

- Competition of SyGuS solvers at FLoC Olympic Games, 30 June 2014
- Competition was conducted offline, using StarExec
- Single track, solvers should support full SyGuS-IF format for the theories of bit-vector and integer linear arithmetic.
- Benchmarks:
  - Bit-manipulation programs from Hacker's delight
  - Integer arithmetic: Find max, search in sorted array
  - Challenge problems such as computing Morton's number
  - Invariant generation problem
  - …

SyGuS

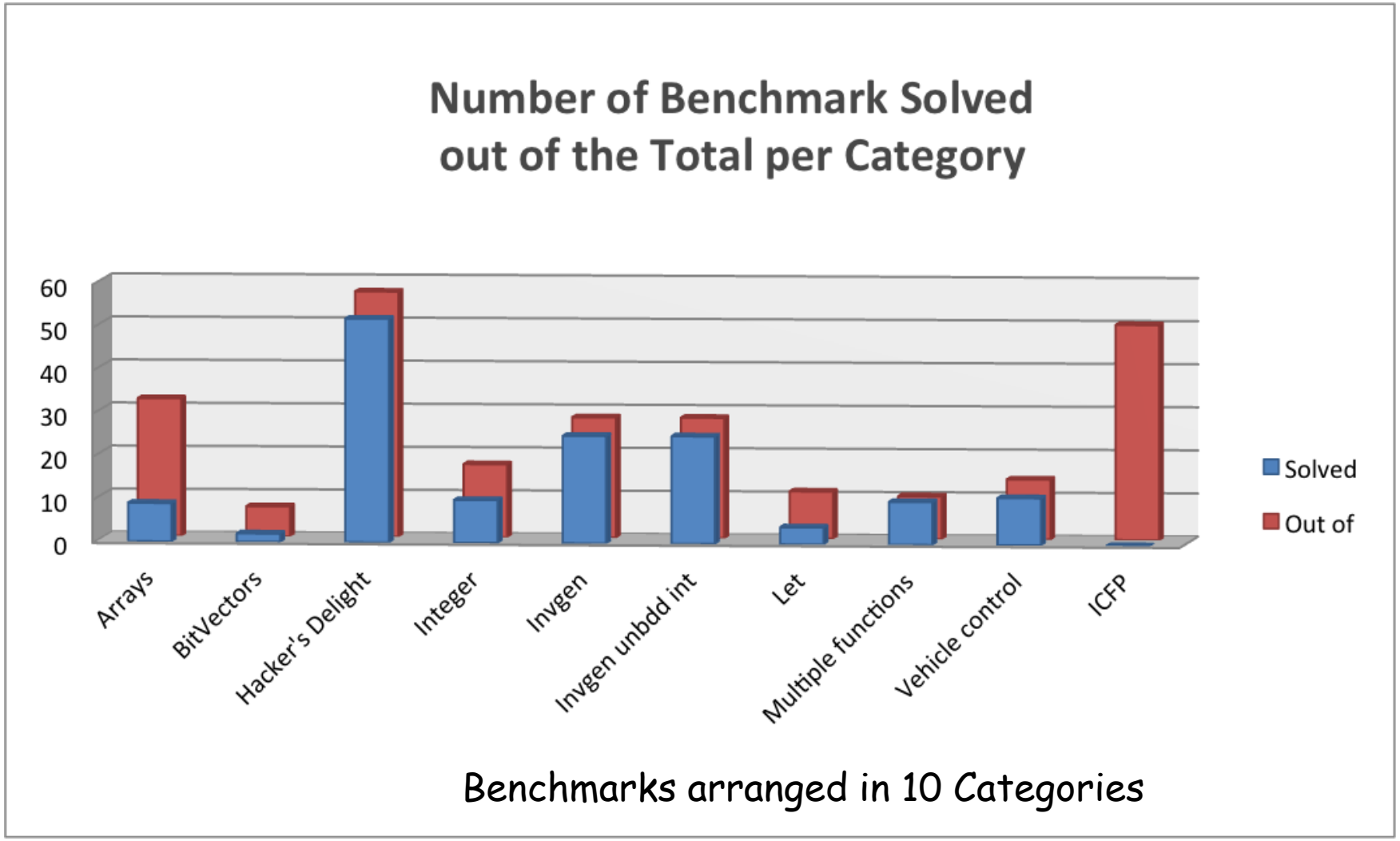
Percentage of Benchmarks Solved

Total:

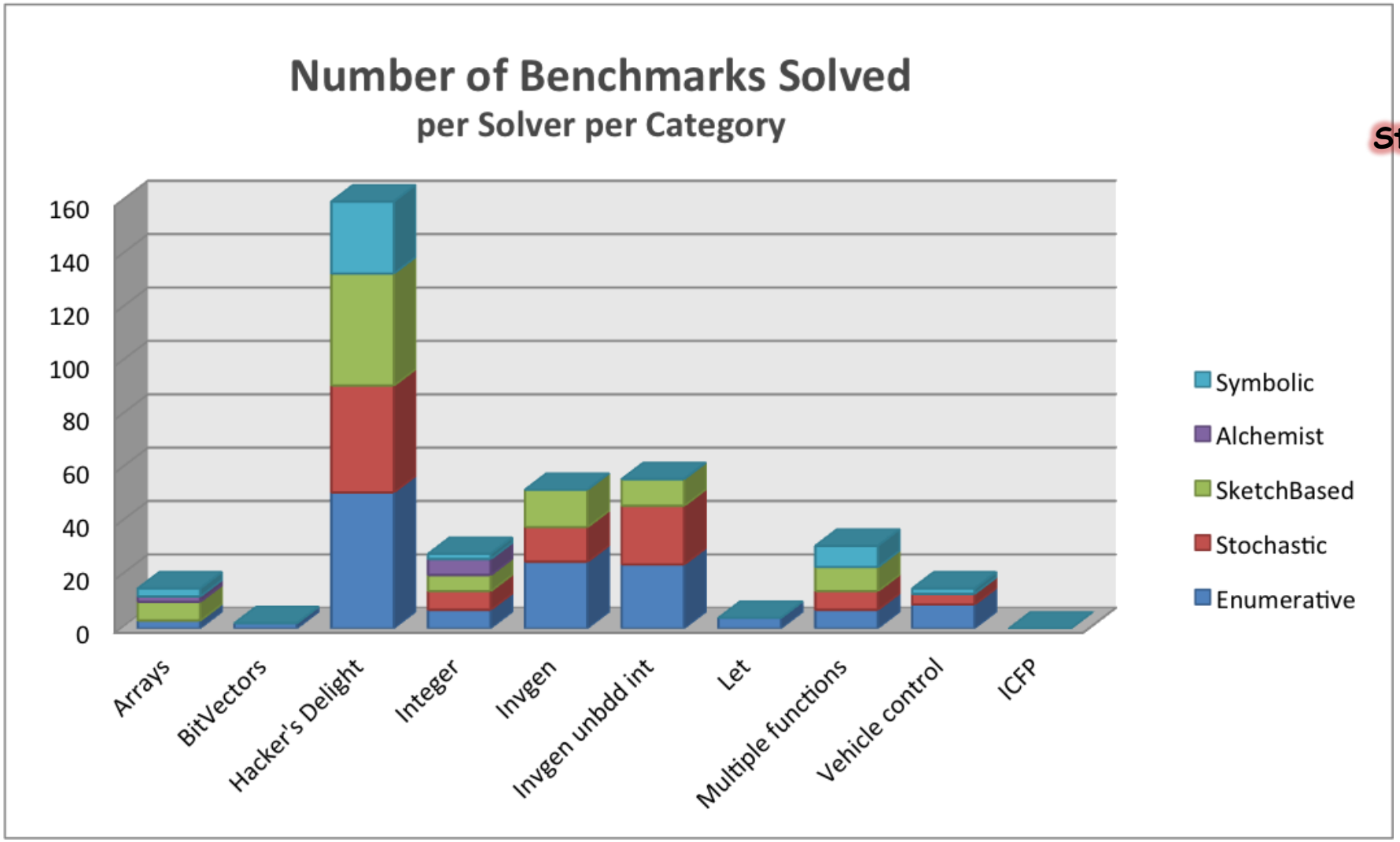
254 benchmarks

Total solved:

148 benchmarks



Number of Benchmarks Solved



5 solvers participated in the competition

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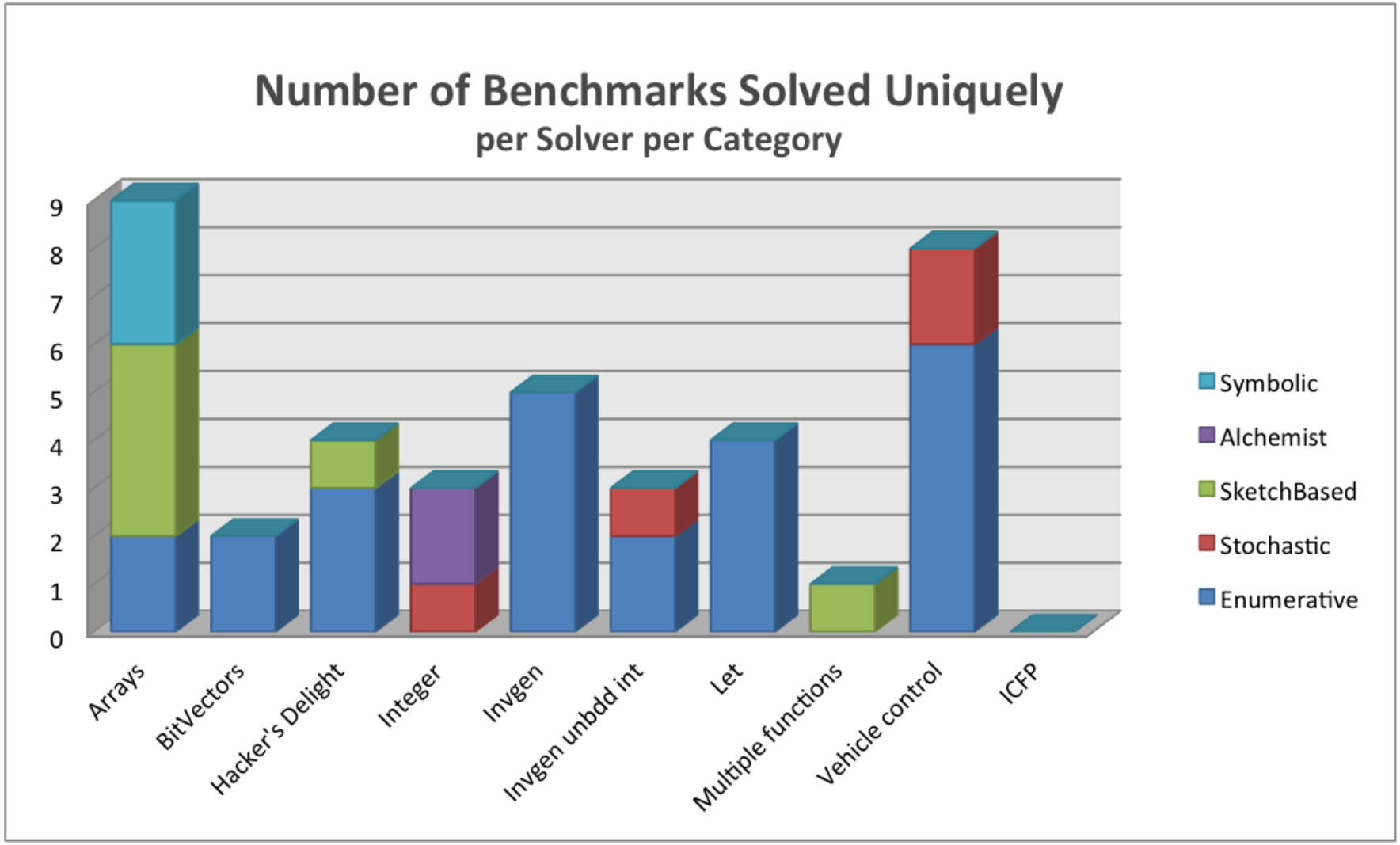
Benchmarks Solved Uniquely



For each of the solvers there were some benchmarks only it solved.

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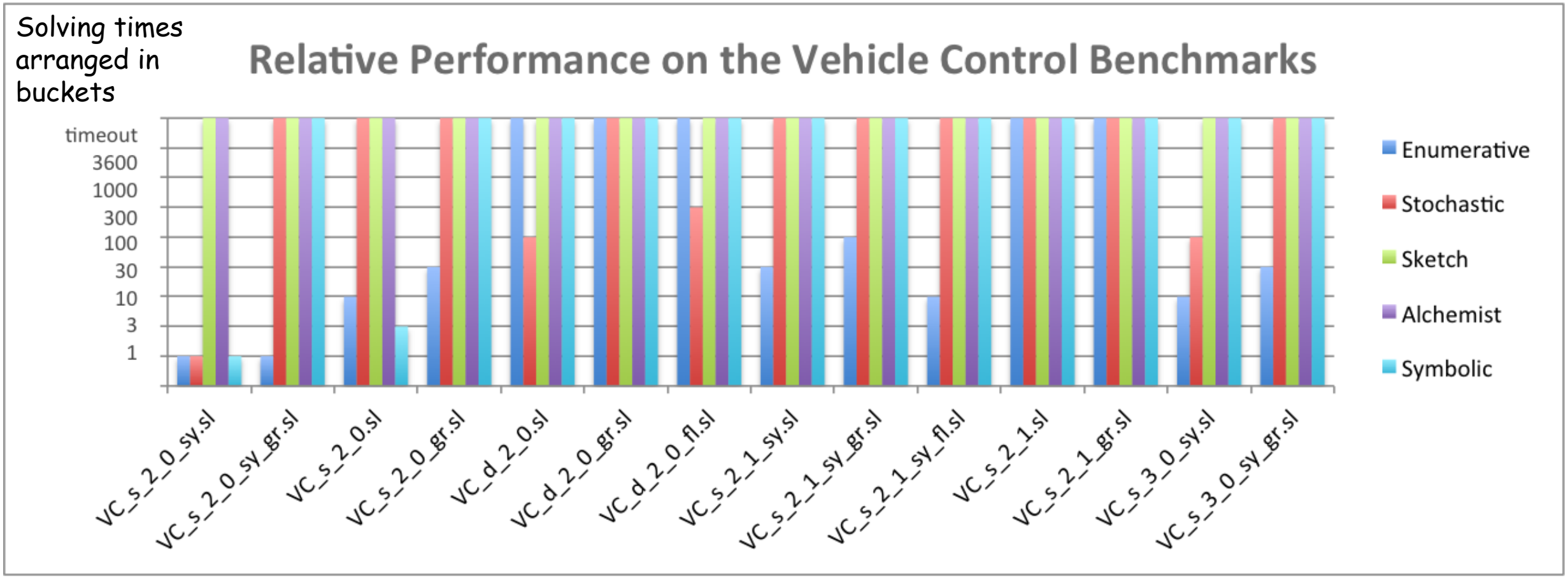
Vehicle Control

Solving times arranged in buckets



Interesting Variations

Benchmark	Enum.	Stoch.	Sket.	Alch.	Symb.	Fastest	Time
array_sum_2_5.sl	-	-	31	139	-	Alchemist	9.012
hd-17-d5-prog.sl	8	73	-	-	9	Enumerative	5.653
LinExpr_eq1.sl	-	-	-	1056	-	Alchemist	1128.870
LinExpr_eq2.sl	-	-	-	180	-	Alchemist	303.780
max4.sl	-	39	-	-	-	Stochastic	95.683
VC22_f2.sl	14	118	-	-	-	Enumerative	5.475
VC22_c2.sl	-	425	-	-	-	Stochastic	128.635
VC22_a_g.sl	6	-	-	-	-	Enumerative	0.016
fivefuncs.sl	-	-	35	-	43	Symbolic	2.540
sixfuncs.sl	-	-	122	-	-	Sketch-based	233.447

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Results Summary

- Enumerative has better performance and solves many benchmarks within seconds (and always produces a minimal expr)

  Potential problem: Synthesis of complex constants

- All solvers succeeded to solve some benchmarks uniquely.

- Choice of grammar has impact on synthesis time

  When E is set of much larger than necessary solvers struggle

- None of the solvers succeed on some benchmarks

  Morton constants, ICFP, Search in integer arrays of size > 4

Bottomline: Improving solvers is a great opportunity for research !

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Future Plans

- Competition on July 2015
- Easier tracks,
  - maybe restricted syntax, only guarded linear expressions
  - only complete specifications
- Suggestions?
  - think of something later?

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The End

Thank you!

Comments or questions?