Syntax-Guided Synthesis

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Program Verification

- \Box Does a program P meet its specification φ ?
- Historical roots: Hoare logic for formalizing correctness of structured programs (late 1960s)
- □ Early examples: sorting, graph algorithms
- Provides calculus for pre/post conditions of structured programs

Sample Proof: Selection Sort



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

Towards Practical Program Verification

- 1. Focus on simpler verification tasks:
 - Not full functional correctness, just absence of specific errors
 - Success story: Array accesses are within bounds
- 2. Provide automation as much as possible
 - Program verification is undecidable
 - Programmer asked to give annotations when absolutely needed
 - Consistency of annotations checked by SMT solvers
- 3. Use verification technology for synergestic tasks
 - Directed testing
 - Bug localization

Selection Sort: Array Access Correctness

```
SelectionSort(int A[],n) {
 i1 :=0;
 while(i1 < n-1) {
  v1 := i1;
  i2 := i1 + 1;
  while (i2 < n) {
    assert (0 \le i2 < n) & (0 \le v1 < n)
    if (A[i2] A[v1])
     v1 := i2 ;
    i2++:
  assert (0 \le i1 < n) & (0 \le v1 < n)
  swap(A[i1], A[v1]);
  i1++:
 return A;
```

Selection Sort: Proving Assertions

```
SelectionSort(int A[],n) {
 i1 :=0;
 while(i1 < n-1) {
   v1 := i1:
  i2 := i1 + 1;
  while (i2 < n) {
    assert 0≤ i2<n & 0≤ v1<n
    if (A[i2] < A[v1])
    v1 := i2 ;
    i2++;
  assert (0 \le i1 < n) & 0 \le v1 < n
  swap(A[i1], A[v1]);
  i1++:
 return A:
```

Check validity of formula

 $(i1 = 0) \& (i1 < n-1) \Rightarrow (0 \le i1 < n)$

And validity of formula

 $(0 \le i1 \le n) \& (i1' = i1+1) \& (i1' \le n-1)$ $\Rightarrow (0 \le i1' \le n)$

Discharging Verification Conditions

- □ Check validity of (i1 = 0) & (i1 < n-1) \Rightarrow (0 ≤ i1 < n)
- □ Reduces to checking satisfiability of (i1 = 0) & (i1 < n-1) & ~(0 ≤ i1 < n)</p>
- □ Core computational problem: checking satisfiability
 - Classical satisfiability: SAT
 Boolean variables + Logical connectives
 - SMT: Constraints over typed variables i1 and n are of type Integer or BitVector[32]

A Brief History of SAT

□ Fundamental Thm of CS: SAT is NP-complete (Cook, 1971)

- Canonical computationally intractable problem
- Driver for theoretical understanding of complexity
- □ Enormous progress in scale of problems that can be solved
 - Inference: Discover new constraints dynamically
 - Exhaustive search with pruning
 - Algorithm engineering: Exploit architecture for speed-up

□ SAT solvers as the canonical computational hammer!



SMT: Satisfiability Modulo Theories

Computational problem: Find a satisfying assignment to a formula

- Boolean + Int types, logical connectives, arithmetic operators
- Bit-vectors + bit-manipulation operations in C
- Boolean + Int types, logical/arithmetic ops + Uninterpreted functs
- □ "Modulo Theory": Interpretation for symbols is fixed
 - Can use specialized algorithms (e.g. for arithmetic constraints)
- □ Progress in improved SMT solvers

Little Engines of Proof

SAT; Linear arithmetic; Congruence closure



Program Synthesis

- □ Classical: Mapping a high-level (e.g. logical) specification to an executable implementation
- □ Benefits of synthesis:
 - Make programming easier: Specify "what" and not "how"
 - Eliminate costly gap between programming and verification
- \square Deductive program synthesis: Constructive proof of Exists f. ϕ







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
```

Automatic Invariant Generation



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

Template-based Automatic Invariant Generation



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Template-based Automatic Invariant Generation



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

Parallel Parking by Sketching

```
Ref: Chaudhuri, Solar-Lezama (PLDI 2010)
```



Autograder: Feedback on Programming Homeworks Singh et al (PLDI 2013)

```
def computeDeriv(poly):
 1
 2
3
4
        deriv = []
        zero = 0
        if (len(poly) == 1):
 5
            return deriv
 6
        for e in range(0,len(poly)):
 7
            if (poly[e] == 0):
 8
                 zero += 1
 9
            else:
10
                 deriv.append(poly[e]*e)
11
        return deriv
```

Student Solution P

- + Reference Solution R
- + Error Model



The program requires 3 changes:

• In the return statement **return deriv** in **line 5**, replace **deriv** by **[0]**.

Find min no of edits to P so as to make it equivalent to R

- In the comparison expression (poly[e] == 0) in line 7, change (poly[e] == 0) to False.
- In the expression range(0, len(poly)) in line 6, replace 0 by 1.

FlashFill: Programming by Examples

Ref: Gulwani (POPL 2011)

Input	Output
(425)-706-7709	425-706-7709
510.220.5586	510-220-5586
1 425 235 7654	425-235-7654
425 745-8139	425-745-8139

- Infers desired Excel macro program
- Iterative: user gives examples and corrections
- Being incorporated in next version of Microsoft Excel

Syntax-Guided Program Synthesis

Core computational problem: Find a program P such that
 1. P is in a set E of programs (syntactic constraint)
 2. P satisfies spec φ (semantic constraint)

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 share benchmarks and/or compare solutions

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
 - Set E of expressions given by a context-free grammar
 Set of candidate expressions that use symbols in T

Computational problem:

Output e in E such that $\varphi[f/e]$ is valid (in theory T)

SyGuS Example

□ Theory QF-LIA

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

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

□ Specification: $(x \le f(x,y)) & (y \le f(x,y)) & (f(x,y) = x | f(x,y)=y)$

Candidate Implementations: Linear expressions LinExp := x | y | Const | LinExp + LinExp | LinExp - LinExp

No solution exists

SyGuS Example

- □ Theory QF-LIA
- \Box Function to be synthesized: f (int x, int y) : int
- □ Specification: $(x \le f(x,y)) & (y \le f(x,y)) & (f(x,y) = x | f(x,y)=y)$
- □ Candidate Implementations: Conditional expressions without +

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

□ Possible solution:

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

Let Expressions and Auxiliary Variables

- □ Synthesized expression maps directly to a straight-line program
- Grammar derivations correspond to expression parse-trees
- □ How to capture common subexpressions (which map to aux vars)?
- □ Solution: Allow "let" expressions
- □ Candidate-expressions for a function f(int x, int y): int T := (let [z = U] in z + z) U := x | y | Const | (U) | U + U | U*U

Optimality

- □ Specification for f(int x): int $x \le f(x) \& -x \le f(x)$
- □ Set E of implementations: Conditional linear expressions
- □ Multiple solutions are possible If-Then-Else (0 ≤ x , x, 0) If-Then-Else (0 ≤ x , x, -x)
- Which solution should we prefer? Need a way to rank solutions (e.g. size of parse tree)

Invariant Generation as SyGuS



Goal: Find inductive loop invariant automatically

Function to be synthesized Inv (bool x, bool z, int a, int b) : bool

Compile loop-body into a logical predicate Body(x,y,z,a,b,c, x',y',z',a',b',c')

□ Specification: Inv & Body & Test' ⇒ Inv'

Template for set of candidate invariants Term := a | b | Const | Term + Term | If-Then-Else (Cond, Term, Term) Cond := x | z | Cond & Cond | ~ Cond | (Cond)

Program Optimization as SyGuS

Type matrix: 2x2 Matrix with Bit-vector[32] entries Theory: Bit-vectors with arithmetic

□ Function to be synthesized f(matrix A, B) : matrix

Specification: f(A,B) is matrix product f(A,B)[1,1] = A[1,1]*B[1,1] + A[1,2]*B[2,1]

Set of candidate implementations
 Expressions with at most 7 occurrences of *
 Unrestricted use of +
 let expressions allowed

Program Sketching as SyGuS

- Sketch programming system
 C program P with ?? (holes)
 Find expressions for holes so as to satisfy assertions
- Each hole corresponds to a separate function symbol
- Specification: P with holes filled in satisfies assertions Loops/recursive calls in P need to be unrolled fixed no of times
- Set of candidate implementations for each hole: All type-consistent expressions
- Not yet explored: How to exploit flexibility of separation beth syntactic and semantic constraints for computational benefits?

Solving SyGuS

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

□ SyGuS can sometimes be reduced to Quantified-SMT, but not always

- Set E is all linear expressions over input vars x, y
 SyGuS reduces to Exists a,b,c. Forall X. φ [f/ ax+by+c]
- Set E is all conditional expressions
 SyGuS cannot be reduced to deciding a formula in LIA
- Syntactic structure of the set E of candidate implementations can be used effectively by a solver
- Existing work on solving Quantified-SMT formulas suggests solution strategies for SyGuS

SyGuS as Active Learning



Concept class: Set E of expressions

Examples: Concrete input values

Counter-Example Guided Inductive Synthesis

□ Concrete inputs I for learning $f(x,y) = \{ (x=a,y=b), (x=a',y=b'), \}$

- \square Learning algorithm proposes candidate expression e such that $\phi[f/e]$ holds for all values in I
- $\hfill\square$ Check if ϕ [f/e] is valid for all values using SMT solver
- \Box If valid, then stop and return e
- □ If not, let (x= α , y= β ,) be a counter-example (satisfies ~ φ [f/e])
- \Box Add (x= α , y= β) to tests I for next iteration

CEGIS Example

□ Specification: $(x \le f(x,y)) & (y \le f(x,y)) & (f(x,y) = x | f(x,y)=y)$

□ Set E: All expressions built from x,y,0,1, Comparison, +, If-Then-Else



CEGIS Example

□ Specification: $(x \le f(x,y)) & (y \le f(x,y)) & (f(x,y) = x | f(x,y)=y)$

□ Set E: All expressions built from x,y,0,1, Comparison, +, If-Then-Else



CEGIS Example

□ Specification: $(x \le f(x,y)) & (y \le f(x,y)) & (f(x,y) = x | f(x,y)=y)$

□ Set E: All expressions built from x,y,0,1, Comparison, +, If-Then-Else



SyGuS Solutions

- □ CEGIS approach (Solar-Lezama, Seshia et al)
- 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): Gulwani et al (PLDI'11)
 - Stochastic (probabilistic walk): Schkufza et al (ASPLOS'13)

Enumerative Learning

□ 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 e₁ and e₂ are equivalent

 if e₁(a,b)=e₂(a,b) on all concrete values (x=a,y=b) in Examples
 Only one representative among equivalent subexpressions needs
 to be considered for building larger expressions

□ Fast and robust for learning expressions with ~ 15 nodes

Symbolic Learning

□ Suppose we know upper bound on no. of occurrences of each symbol



Variables encode edges in desired expression tree
 E.g. 19, r9 : {n1, ... n10} give left and right children of node n9

Constraints: Types are consistent, Shape is a DAG Spec φ[f/e] is satisfied on every concrete input values in I

Use an SMT solver to find a satisfying solution

□ If unsatisfied, then bounds need to be increased in outer loop

Stochastic Learning

- Idea: Find desired expression e by probabilistic walk on graph where nodes are expressions and edges capture single-edits
- □ For a given set I of concrete inputs, Score(e) = exp(0.5 Wrong(e)), where Wrong(e) = No of examples in I for which ~ φ [f/e]
- \square Fix n and consider E_n to be set of all expressions in E of size n
- \Box Initialize: Choose e by uniform sampling of E_n

If Score(e)=1 then return e, else:
 Choose a node v in parse-tree of e at random
 Replace subtree at v by a random subtree of same size to get e'
 Update e to e' with probability min{ 1, Score(e')/Score(e) }

Outer loop responsible for updating expression size n

Benchmarks and Implementation

- □ Prototype implementation of Enumerative/Symbolic/Stochastic CEGIS
- Benchmarks:
 - Bit-manipulation programs from Hacker's delight
 - Integer arithmetic: Find max, search in sorted array
 - Challenge problems such as computing Morton's number
- □ Multiple variants of each benchmark by varying grammar
- Results are not conclusive as implementations are unoptimized, but offers first opportunity to compare solution strategies

Evaluation

 Enumerative CEGIS has best performance, and solves many benchmarks within seconds
 Potential problem: Synthesis of complex constants

Symbolic CEGIS is unable to find answers on most benchmarks Caveat: Sketch succeeds on many of these

Choice of grammar has impact on synthesis time When E is set of all possible expressions, solvers struggle

None of the solvers succeed on some benchmarks Morton constants, Search in integer arrays of size > 4

Bottomline: Improving solvers is a great opportunity for research !

SyGuS Recap

□ Contribution: Formalization of syntax-guided synthesis problem

- Not language specific such as Sketch, Scala^Z3,...
- Not as low-level as (quantified) SMT
- Advantages compared to classical synthesis
 - 1. Set E can be used to restrict search (computational benefits)
 - 2. Programmer flexibility: Mix of specification styles
 - 3. Set E can restrict implementation for resource optimization
 - 4. Beyond deductive solution strategies: Search, inductive inference
- Prototype implementation of 3 solution strategies
- $\hfill\square$ Initial set of benchmarks and evaluation

From SMT-LIB to SYNTH-LIB

```
(set-logic LIA)
(synth-fun max2 ((x Int) (y Int)) Int
   ((Start Int (x y 0 1
               (+ Start Start)
               (- Start Start)
               (ite StartBool Start Start)))
    (StartBool Bool ((and StartBool StartBool)
                      (or StartBool StartBool)
                      (not StartBool)
                     (<= Start Start))))
(declare-var x Int)
(declare-var y Int)
(constraint (>= (max2 x y) x))
(constraint (>= (max2 x y) y))
(constraint (or (= x (max2 x y)) (= y (max2 x y))))
(check-synth)
```

Plan for Synth-Comp

- □ Proposed competition of SyGuS solvers at FLoC, July 2014
- □ Organizers: Alur, Fisman (Penn) and Singh, Solar-Lezama (MIT)
- □ Website: excape.cis.upenn.edu/Synth-Comp.html
- □ Mailing list: <u>synthlib@cis.upenn.edu</u>
- □ Call for participation:
 - Join discussion to finalize synth-lib format and competition format
 - Contribute benchmarks
 - Build a SyGuS solver

