Automatically Generating Search Heuristics for Concolic Testing (+ program analysis, synthesis, and repair)

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Our Research

- We research on technology for safe and reliable software.
- Research areas: programming languages, software engineering, software security
 - software analysis and testing
 - software synthesis and repair
- Publication: top-venues in PL, SE, and Security
 - PLDI('12,'14), ICSE'17,
 OOPSLA('15,'17,'17), S&P'17, etc



Our Long-term Goal

 Achieving technologies for automatically finding, verifying, and fixing software errors and vulnerabilities



Today: Concolic Testing

• Concolic testing is an effective software testing method based on symbolic execution



- Key challenge: path explosion
- Our solution: mitigate the problem with good search heuristics

Limitation of Random Testing

```
int double (int v) {
   return 2*v;
}
```

void testme(int x, int y) {

```
z := double (y);
```

```
if (z==x) {
```

Probability of the error? ($0 \le x, y \le 100$)

Limitation of Random Testing

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< 0.4%

- random testing requires 250 runs
- concolic testing finds it in 3 runs











2nd iteration



















execution tree

Concolic Testing b_1 **b**₂ solve $(\neg b_1)$ **b**4 **b**₃ **b**5 Ф2

execution tree



execution tree

Concolic Testing Algorithm

Input :Program *P*, initial input vector v_0 , budget *N* **Output**:The number of branches covered

1:
$$T \leftarrow \langle \rangle$$

2:
$$v \leftarrow v_0$$

3: **for**
$$m = 1$$
 to N **do**

4:
$$\Phi_m \leftarrow \text{RunProgram}(P, v)$$

5:
$$T \leftarrow T \cdot \Phi_m$$

6: repeat

7:
$$(\Phi, \phi_i) \leftarrow \text{Choose}(T) \qquad (\Phi = \phi_1 \land \cdots \land \phi_n)$$

8: **until** SAT
$$(\bigwedge_{j < i} \phi_j \land \neg \phi_i)$$

9:
$$v \leftarrow \operatorname{model}(\bigwedge_{j < i} \phi_j \land \neg \phi_i)$$

10: **end for**

11: **return** |Branches(T)|

Concolic Testing Algorithm

ch

 $\wedge \phi_n$)

Heuristic

Input :Program *P*, initial input vector v_0 , budget *N* **Output**:The number of branches covered

1:
$$T \leftarrow \langle \rangle$$

2:
$$v \leftarrow v_0$$

3: **for**
$$m = 1$$
 to N **do**

4:
$$\Phi_m \leftarrow \text{RunProgram}(P)$$
 Sear

5:
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6: repeat

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8: **until** SAT
$$(\bigwedge_{j < i} \phi_j \land \neg \phi_i)$$

9: $v \leftarrow \operatorname{model}(\bigwedge_{j < i} \phi_j \land \neg \phi_i)$

10: **end for**

11: **return** |Branches(T)|

Path Explosion

• Concolic testing relies on search heuristics to maximize code coverage in a limited budget.



Existing Search Heuristics

- Numerous heuristics have been proposed, e.g.,
 - DFS, BFS, Random, Generational, CFDS, CGS, etc
- CFDS (Control-Flow-Directed Search) [1]
 - selects a branch whose opposite branch is the nearest from the unseen branches
- CGS (Context-Guided Search) [2]
 - basically performs BFS while excluding branches whose contexts are previously explored

^[1] J. Burnim and K. Sen. Heuristics for Scalable Dynamic Test Generation. ASE 2008.

^[2] Hyunmin Seo and Sunghun Kim. How we get there: A context-guided search strategy in con colic testing. FSE 2014 24

Limitations of Existing Search Heuristics

 No existing heuristics consistently perform well in practice



Limitations of Existing Search Heuristics

- Furthermore, manually developing a search heuristic is nontrivial, requiring a huge amount of engineering effort and expertise.
- Ordinary developers and testers cannot fully benefit from concolic testing technology.

Our goal: automatically generating search heuristics

• Considerable increase in branch coverage



• Considerable increase in branch coverage



• Dramatic increase in bug-finding capability

	OURS	CFDS	CGS	Random	Gen	DFS
gawk-3.0.3	100/100	0/100	0/100	0/100	0/100	0/100
grep-2.2	85/100	0/100	7/100	0/100	0/100	0/100

Key Ideas

- Parameterization of search heuristics
- Searching good parameters for

Parameterization?

• Fixed (non-parameterized) heuristics define single instances of search heuristics:

Choose ∈ *SearchHeuristic*

ex) DFS

 $\mathsf{Choose}(\langle \Phi_1 \Phi_2 \cdots \Phi_m \rangle) = (\Phi_m, \phi_{|\Phi_m|})$

• Parameterized heuristic defines a class of search heuristics:

 $Choose_{\theta} \subseteq SearchHeuristic$

Our Parameterized Search Heuristic

 $Choose_{\theta}(\langle \Phi_1 \cdots \Phi_m \rangle) = (\Phi_m, \operatorname{argmax} score_{\theta}(\phi_j))$ $\phi_j \in \Phi_m$



(I) Feature Extraction

• A feature is a predicate on branches:

 $\pi_i : Branch \rightarrow \{0, 1\}$

e.g., whether the branch is located in a loop

• Represent a branch by a feature vector

$$\pi(\phi) = \langle \pi_1(\phi), \pi_2(\phi), \dots, \pi_k(\phi) \rangle$$

• Example

 $\pi(b_1) = \langle 1, 0, 1, 1, 0 \rangle$ $\pi(b_4) = \langle 0, 1, 1, 1, 0 \rangle$ $\pi(b_5) = \langle 1, 0, 0, 0, 1 \rangle$

Branch Features

• 12 static features

- extracted without execution
- 28 dynamic features
 - extracted at runtime

#	Description
1	branch in the main function
2	true branch of a loop
3	false branch of a loop
4	nested branch
5	branch containing external function calls
6	branch containing integer expressions
7	branch containing constant strings
8	branch containing pointer expressions
9	branch containing local variables
10	branch inside a loop body
11	true branch of a case statement
12	false branch of a case statement
13	first 10% branches of a path
14	last 10% branches of a path
15	branch appearing most frequently in a path
16	branch appearing least frequently in a path
17	branch newly covered in the previous execution
18	branch located right after the just-negated branch
19	branch whose context ($k = 1$) is already visited
20	branch whose context ($k = 2$) is already visited
21	branch whose context ($k = 3$) is already visited
22	branch whose context ($k = 4$) is already visited
23	branch whose context ($k = 5$) is already visited
24	branch negated more than 10 times
25	branch negated more than 20 times
26	branch negated more than 30 times
27	branch near the just-negated branch
28	branch failed to be negated more than 10 times
29	the opposite branch failed to be negated more than 10 times
30	the opposite branch is uncovered (depth 0)
31	the opposite branch is uncovered (depth 1)
32	branch negated in the last 10 executions
33	branch negated in the last 20 executions

32

(2) Scoring

• The parameter is a k-length vector of real numbers

 $\theta = \langle 0.8, -0.5, 0.3, 0.2, -0.7 \rangle$

• Compute score by linear combination of feature vector and parameter

$$score_{\theta}(\phi) = \pi(\phi) \cdot \theta$$

score_{θ}(b₁) = $\langle 1,0,1,1,0 \rangle \cdot \langle 0.8,-0.5,0.3,0.2,-0.7 \rangle = 1.3$ score_{θ}(b₄) = $\langle 0,1,1,1,0 \rangle \cdot \langle 0.8,-0.5,0.3,0.2,-0.7 \rangle = 0.0$ score_{θ}(b₅) = $\langle 1,0,0,0,1 \rangle \cdot \langle 0.8,-0.5,0.3,0.2,-0.7 \rangle = 0.1$

Optimization Algorithm

• Finding a good search heuristic reduces to solving the optimization problem:

 $\operatorname{argmax} C(P, \operatorname{Choose}_{\theta})$ $\theta \in \mathbb{R}^k$

where

 $C: Program \times SearchHeuristic \rightarrow \mathbb{N}$

Naive Algorithm

• Naive algorithm based on random sampling

1: repeat

- 2: $\theta \leftarrow \text{sample from } \mathbb{R}^k$
- 3: $B \leftarrow C(P, \text{Choose}_{\theta})$
- 4: **until** timeout
- 5: **return** best θ found
- Failed to find good parameters
 - Search space is intractably large
 - Inherent performance variation in concolic testing

Our Algorithm

 Iteratively refine the sample space based on the feedback from previous runs of concolic testing



Experiments

- Implemented in CREST
- Compared with five existing heuristics
 - CGS, CFDS, Random, DFS, Generational
- 10 open-source programs

Program	# Total branches	LOC
vim-5.7	35,464	165K
gawk-3.0.3	8,038	30K
expat-2.1.0	8,500	49K
grep-2.2	3,836	15K
sed-1.17	2,565	9K
tree-1.6.0	1,438	4K
cdaudio	358	3K
floppy	268	2K
kbfiltr	204	1K
replace	196	0.5K

Evaluation Setting

- The same initial inputs
- The same testing budget (4,000 executions)
- Performance averaged over 100 trials (20 for vim)

• Average branch coverage (on large programs)



• Maximum branch coverage

	OURS	CFDS	CGS	Random	Gen	DFS
vim	8,744	8,322	6,150	7,645	5,092	2,646
expat	1,422	1,060	1,337	965	1,348	1,027
gawk	2,684	2,532	2,449	2,035	2,443	1,025
grep	1,807	1,726	1,751	1,598	1,640	1,456
sed	830	780	781	690	698	568
tree	797	702	599	704	600	360

• On small benchmarks

	OURS	CFDS	CGS	Random	Gen	DFS
cdaudio	250	250	250	242	236	250
floppy	205	205	205	170	168	205
replace	181	177	181	174	171	176
kbfiltr	149	149	149	149	134	149

• Higher branch coverage leads to much more effective finding of real bugs

	OURS	CFDS	CGS	Random	Gen	DFS
gawk-3.0.3	100/100	0/100	0/100	0/100	0/100	0/100
grep-2.2	85/100	0/100	7/100	0/100	0/100	0/100

• Our heuristics are much better than others in exercising diverse program paths

Training Overhead

• Time for obtaining the heuristics (with 20 cores)

Benchmarks	# Sample	# Iteration	Total times
vim-5.7	300	5	24h 18min
expat-2.1.0	1,000	6	10h 25min
gawk-3.0.3	1,000	4	6h 30min
grep-2.2	1,000	5	5h 24min
sed-1.17	1,000	4	8h 54min
tree-1.6.0	1,000	4	3h 18min

Still useful

• Concolic testing is run in the training phase

	OURS	CFDS	CGS	Random	Gen	DFS
vim	14,003	13,706	7,934	13,835	7,290	7,934
expat	2,455	2,339	2,157	1,325	2,116	2,036
gawk	3,473	3,382	3,261	3,367	3,302	1,905
grep	2,167	2,024	2,016	2,066	1,965	1,478
sed	1,019	1,041	1,042	1,007	979	937
tree	808	800	737	796	730	665

Still useful

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Other On-Going Projects (program analysis, synthesis, and repair)

Static Program Analysis

Technology for "Software MRI"



- Detect software defects statically and automatically
- Being widely used in sw industry



Towards More Sound, Precise, and Scalable Static Analysis

No existing technologies achieve the three



Towards More Sound, Precise, and Scalable Static Analysis

Our direction: selective program analysis



Selectively Unsound Analysis

• Selectively apply unsoundness only when harmless

			BASE	ELINE	Seli	ECTIVE	Unif	FORM
Program	LOC	Bug	Т	F	Τ	F	Т	F
mp3rename-0.6	0.6K	1	1	0	1	0	1	0
ghostscript-8.71	1.5K	2	2	0	2	0	2	0
uni2ascii-4.14	5.7K	7	7	0	7	0	7	0
pal-0.4.3	7.4K	3	3	0	0	0	0	0
shntool-3.0.1	16.3K	1	1	10	1	1	1	0
sdop-0.61	23.9K	65	65	78	65	0	0	0
latex2rtf-2.3.8	28.7K	2	2	9	2	8	0	1
rrdtool-1.4.8	34.8K	1	1	12	1	1	1	0
daemon-0.6.4	58.4K	1	1	7	1	1	1	0
rplay-3.3.2	61.0K	3	3	7	2	4	1	2
urjtag-0.10	64.2K	12	12	78	6	0	0	0
a2ps-4.14	64.6K	6	6	26	3	12	1	0
dico-2.0	84.3K	2	2	46	1	1	1	2
Total		106	106	273	92	28	16	5

Our Approaches to Selective Program Analysis

- Pre-analysis approach
 - Selective context-sensitivity [PLDI'14]
- Data-driven approach
 - Selective flow-sensitivity [OOPSLA'I5]
 - Selective relational analysis [SAS'16]
 - Selective unsoundness [ICSE'17]
 - Disjunctive model and algorithm [OOPSLA'17a]
 - Automatic feature construction [OOPSLA'17b]

Program Analysis vs. Synthesis

- Program Analysis derives specifications from code
- Program Synthesis derives code from specifications

Program Synthesis

- Generate program code from specifications automatically
 - specification: logics, examples, implementation, etc
- Applications
 - programming assistance: e.g., complete tricky parts of programs
 - end-user programming: e.g., automate repetitive tasks
 - algorithm discovery: find a new solution for a problem
 - automatic patch generation: automatically fix software bugs

Example

• Specification is given as test cases

reverse(12) = 21, reverse(123) = 321



Status

Better than humans for introductory programming tasks

Domain	No	Description		Vars		Ints Exs Time (sec)		Time (sec)	
Domain		Description	IVars	AVars	Ints	LAS	Base	Base+Opt	Ours
	1	Given <i>n</i> , return <i>n</i> !.	2	0	2	4	0.0	0.0	0.0
	2	Given n , return $n!!$ (i.e., double factorial).	3	0	3	4	0.0	0.0	0.0
	3	Given <i>n</i> , return $\sum_{i=1}^{n} i$.	3	0	2	4	0.1	0.0	0.0
	4	Given <i>n</i> , return $\sum_{i=1}^{n} i^2$.	4	0	2	3	122.4	18.1	0.3
	5	Given <i>n</i> , return $\prod_{i=1}^{n} i^2$.	4	0	2	3	102.9	13.6	0.2
	6	Given a and n , return a^n .	4	0	2	4	0.7	0.1	0.1
	7	Given n and m, return $\sum_{i=n}^{m} i$.	3	0	2	3	0.2	0.0	0.0
Integer	8	Given n and m, return $\prod_{i=n}^{m} i$.	3	0	2	3	0.2	0.0	0.1
muger	9	Count the number of digit for an integer.	3	0	3	3	0.0	0.0	0.0
	10	Sum the digits of an integer.	3	0	3	4	5.2	2.2	1.3
	11	Calculate product of digits of an intger.	3	0	3	3	0.7	2.3	0.3
	12	Count the number of binary digit of an integer.	2	0	3	3	0.0	0.0	0.0
	13	Find the <i>n</i> th Fibonacci number.	3	0	3	4	98.7	13.9	2.6
	14	Given <i>n</i> , return $\sum_{i=1}^{n} (\sum_{m=1}^{i} m)$).	3	0	2	4	\perp	324.9	37.6
	15	Given <i>n</i> , return $\prod_{i=1}^{n} (\prod_{m=1}^{i} m)$).	3	0	2	4	\perp	316.6	86.9
	16	Reverse a given integer.	3	0	3	3	\perp	367.3	2.5
	17	Find the sum of all elements of an array.	3	1	2	2	8.1	3.6	0.9
	18	Find the product of all elements of an array.	3	1	2	2	7.6	3.9	0.9
	19	Sum two arrays of same length into one array.	3	2	2	2	44.6	29.9	0.2
	20	Multiply two arrays of same length into one array.	3	2	2	2	47.4	26.4	0.3
	21	Cube each element of an array.	3	1	1	2	1283.3	716.1	13.0
	22	Manipulate each element into 4th power.	3	1	1	2	1265.8	715.5	13.0
	23	Find a maximum element.	3	1	2	2	0.9	0.7	0.4
Array	24	Find a minimum element.	3	1	2	2	0.8	0.3	0.1
Allay	25	Add 1 to each element.	2	1	1	3	0.3	0.0	0.0
	26	Find the sum of square of each element.	3	1	2	2	2700.0	186.2	11.5
	27	Find the multiplication of square of each element.	3	1	1	2	1709.8	1040.3	12.6
	28	Sum the products of matching elements of two arrays.	3	2	1	3	20.5	38.7	1.5
	29	Sum the absolute values of each element.	2	1	1	2	45.0	50.5	12.1
	30	Count the number of each element.	3	1	3	2	238.9	1094.1	0.2
Average > 616.8 165									

 Memory management errors (memory leak, useafter-free, double free) are common:

	-Statistics of common bug types-									
	StackOverflow	CitHub	Tizen							
	StackOvernow	Gittub	CodeReview							
BO	10,099	586, 385	155							
IO	11,356	$594,\!032$	15							
ND	$3,\!592$	755,354	220							
MM	107,869	$3,\!804,\!869$	1,320							

< Statistics of common bug types>

*BO/IO: Buffer/Integer-overflow *ND: Null-dereference *MM: Memory management errors

Manual repair is error-prone, requiring multiple iterations of review process



- Automatically patching memory management errors
- Patched programs are guaranteed to be error-free



• Combination of program analysis and synthesis



Automatic Feedback Generation

- In typical programming courses (e.g., MOOC):
 - students receive no personalized feedback
 - solutions are not much helpful





```
let rec map f (l,var) =
    match l with
    [] -> []
    | hd::tl -> (f (hd,var))::(map f (tl,var))
...
| Sum lst -> Sum (map diff (lst,var))
...
```

Automatic Feedback Generation



- Error localization by MAX-SAT solving
- Correction by program synthesis

Summary

 Technologies for automatically finding, verifying, and fixing software errors and vulnerabilities



Summary

 Technologies for automatically finding, verifying, and fixing software errors and vulnerabilities

