

Dynamically Detecting Likely Program Invariants

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Overview

Goal: recover invariants from programs

Technique: run the program, examine values

Artifact: Daikon

Results: • recovered formal specifications
• aided in a software modification task

Outline: • motivation
• techniques
• future work

Goal: recover invariants

Detect invariants like those in **assert** statements

- **$x > \text{abs}(y)$**
- **$x = 16*y + 4*z + 3$**
- array ***a*** contains no duplicates
- for each node ***n***, **$n = n.\text{child}.\text{parent}$**
- graph ***g*** is acyclic

Uses for invariants

Write better programs [Liskov 86]

Documentation

Convert to **assert**

Maintain invariants to avoid introducing bugs

Validate test suite: value coverage

Locate exceptional conditions

Higher-level profile-directed compilation
[Calder 98]

Bootstrap proofs [Wegbreit 74, Bensalem 96]

Experiment 1:

recover formal specifications

Example: Program 15.1.1
from *The Science of Programming* [Gries 81]

// Sum array b of length n into variable s .

$i := 0; s := 0;$

while $i \neq n$ **do**

$\{ s := s + b[i]; i := i + 1 \}$

Precondition: $n \geq 0$

Postcondition: $s = (\sum j: 0 \leq j < n : b[j])$

Loop invariant: $0 \leq i \leq n$ and $s = (\sum j: 0 \leq j < i : b[j])$

Test suite for program 15.1.1

100 randomly-generated arrays

- Length uniformly distributed from 7 to 13
- Elements uniformly distributed from -100 to 100

Inferred invariants

15.1.1:::BEGIN	(100 samples)
N = size(B)	(7 values)
N in [7..13]	(7 values)
B	(100 values)
All elements in [-100..100]	(200 values)
15.1.1:::END	(100 samples)
N = I = N_orig = size(B)	(7 values)
B = B_orig	(100 values)
S = sum(B)	(96 values)
N in [7..13]	(7 values)
B	(100 values)
All elements in [-100..100]	(200 values)

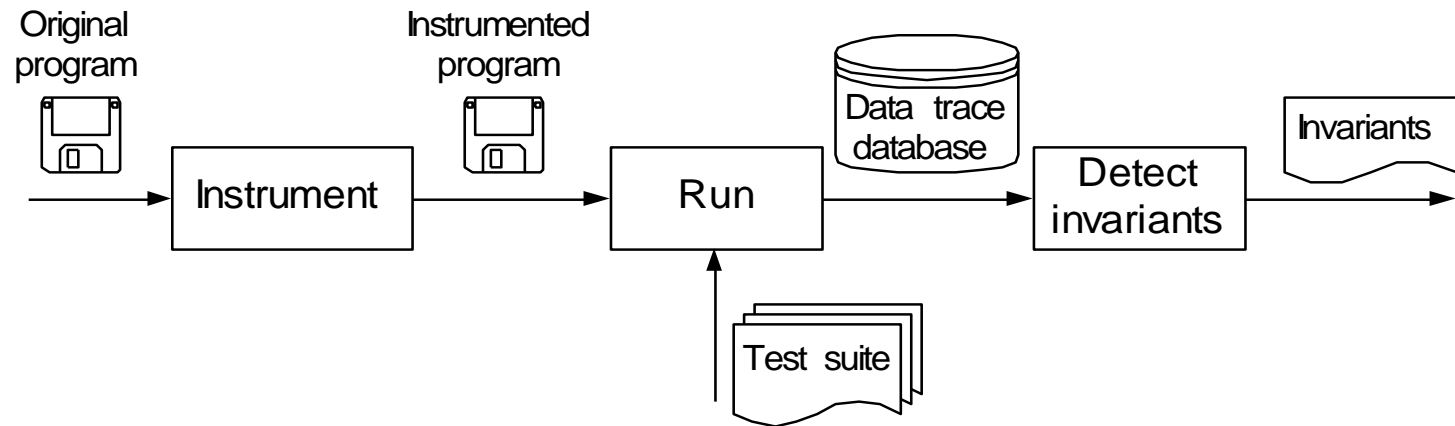
Inferred loop invariants

15.1.1:::LOOP	(1107 samples)
N = size(B)	(7 values)
S = sum(B[0..I-1])	(96 values)
N in [7..13]	(7 values)
I in [0..13]	(14 values)
I <= N	(77 values)
B	(100 values)
All elements in [-100..100]	(200 values)
B[0..I-1]	(985 values)
All elements in [-100..100]	(200 values)

Ways to obtain invariants

- Programmer-supplied
- Static analysis: examine the program text
[Cousot 77, Gannod 96]
 - properties are guaranteed to be true
 - pointers are intractable in practice
- Dynamic analysis: run the program

Dynamic invariant detection



Look for patterns in values the program computes:

- Instrument the program to write data trace files
- Run the program on a test suite
- Offline invariant engine reads data trace files, checks for a collection of potential invariants

Running the program

Requires a test suite

- standard test suites are adequate
- relatively insensitive to test suite

No guarantee of completeness or soundness

- useful nonetheless

Sample invariants

x, y, z are variables; a, b, c are constants

Numbers:

- unary: $x = a$, $a \leq x \leq b$, $x \equiv a \pmod{b}$
- n-ary: $x \leq y$, $x = ay + bz + c$, $x = \max(y, z)$

Sequences:

- unary: sorted, invariants over all elements
- with scalar: membership
- with sequence: subsequence, ordering

Checking invariants

For each potential invariant:

- quickly determine constants
(e.g., a and b in $y = ax + b$)
- stop checking once it is falsified

This is inexpensive

Performance

Runtime growth:

- quadratic in number of variables at a program point
(linear in number of invariants checked/discovered)
- linear in number of samples or values (test suite size)
- linear in number of program points

Absolute runtime: a few minutes per procedure

- 10,000 calls, 70 variables, instrument entry and exit

Statistical checks

Check hypothesized distribution

To show $x \neq 0$ for v values of x in range of size r ,
probability of no zeroes is $\left(1 - \frac{1}{r}\right)^v$

Range limits (e.g., $x \geq 22$):

- more samples than neighbors (clipped to that value)
- same number of samples as neighbors (uniform distribution)

Derived variables

Variables not appearing in source text

- array: length, sum, min, max
- array and scalar: element at index, subarray
- number of calls to a procedure

Enable inference of more complex relationships

Staged derivation and invariant inference

- avoid deriving meaningless values
- avoid computing tautological invariants

Experiment 2: C code lacking explicit invariants

563-line C program: regexp search & replace

[Hutchins 94, Rothermel 98]

Task: modify to add Kleene +

Use both detected invariants and traditional tools

Experiment 2 invariant uses

Contradicted some maintainer expectations

anticipated $lj < j$ in `makepat`

Revealed a bug

when $lastj = *j$ in `stclose`, array bounds error

Explicated data structures

regex compiled form (a string)

Experiment 2 invariant uses

Showed procedures used in limited ways

makepat: $start = 0$ and $delim = '\backslash 0'$

Demonstrated test suite inadequacy

$calls(in_set_2) = calls(stclose)$

Changes in invariants validated program changes

stclose: $*j = *j_{orig} + 1$ **plclose:** $*j \geq *j_{orig} + 2$

Experiment 2 conclusions

Invariants:

- effectively summarize value data
- support programmer's own inferences
- lead programmers to think in terms of invariants
- provide serendipitous information

Useful tools:

- trace database (supports queries)
- invariant differencer

Future work

Logics:

- Disjunctions: $p = \text{NULL}$ or $*p > i$
- Predicated invariants: *if condition then invariant*
- Temporal invariants
- Global invariants (multiple program points)
- Existential quantifiers

Domains: recursive (pointer-based) data structures

- Local invariants
- Global invariants: structure [Hendren 92], value

More future work

User interface

- control over instrumentation
- display and manipulation of invariants

Experimental evaluation

- apply to a variety of tasks
- apply to more and bigger programs
- users wanted! (Daikon works on C, C++, Java, Lisp)

Related work

Dynamic inference

- inductive logic programming [Bratko 93]
- program spectra [Reps 97]
- finite state machines [Boigelot 97, Cook 98]

Static inference [Jeffords 98]

- checking specifications [Detlefs 96, Evans 96, Jacobs 98]
- specification extension [Givan 96, Hendren 92]
- etc. [Henry 90, Ward 96]

Conclusions

Dynamic invariant detection is feasible

- Prototype implementation

Dynamic invariant detection is effective

- Two experiments provide preliminary support

Dynamic invariant detection is a challenging but promising area for future research