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 > abs(y)`**
- **`x = 16*y + 4*z + 3`**
- array **`a`** contains no duplicates
- for each node **`n`**, **`n = n.child.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: $s = (\Sigma j : 0 \leq j < n : b[j])$

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

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)
```

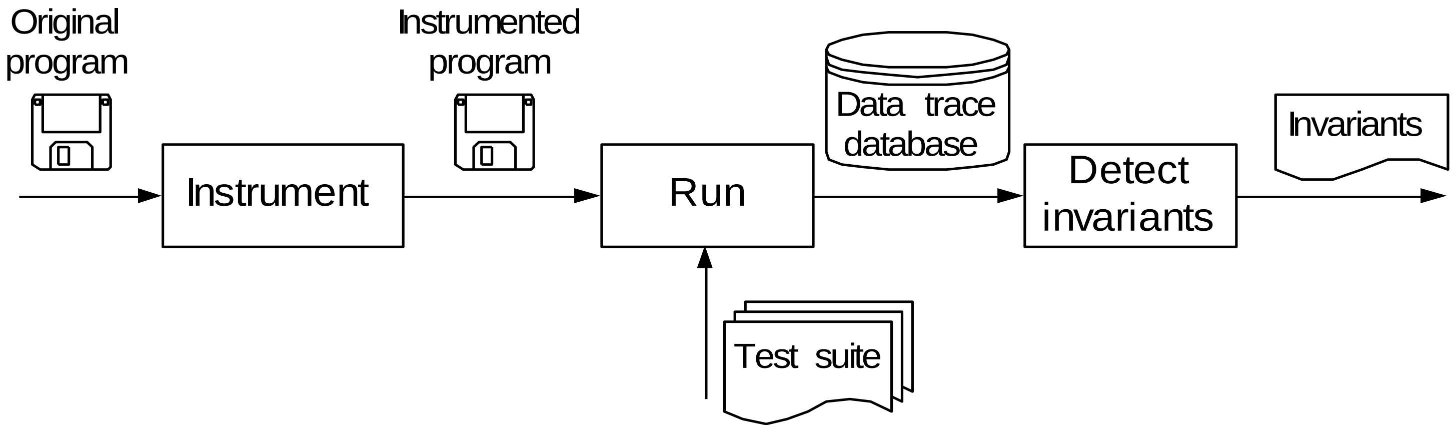
Inferred loop invariants

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

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
    - regexp compiled form (a string)

Experiment 2 invariant uses

Showed procedures used in limited ways

- **`makepat`**: start = 0 and delim = '\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 = 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