Directed Automated Randomized Testing (DART)

Motivation

Verification is *really* hard

Unit testing is also hard and rarely done properly

- Have to check all corner cases
- Have to simulate external environment
- Have to set up a driver

Static analysis is imprecise

Tools like lint generate a lot of false positives

What does DART do?

Automatically extracts a programs interface

Automatically generates a test driver for all externally visible functions

Automatically performs randomized testing

Randomized testing produces poor coverage

Overview

- .. Start with randomized input
- . Determine predicates that must be satisfied to enter conditionals
- 6. Generate new input satisfying these constraints
- Repeat until all paths have been traversed

Program Model

Random Access Memory (RAM) Machine:

- A Memory M is a mapping between address and 32 bit words
- + denotes updating; M' = M + [m -> v] means replace value at m with v

DART models

- Symbolic memory S, which maps addresses to expressions
- Concrete memory M, which maps addresses to concrete values

A program consists of statements which can either be:

- Assignment
- Conditional

The instrumented program

```
ase (m \leftarrow e):
S = S + [m \mapsto evaluate\_symbolic(e, \mathcal{M}, \mathcal{S})]
v = evaluate\_concrete(e, \mathcal{M})
\mathcal{M} = \mathcal{M} + [m \mapsto v]; \ell = \ell + 1
ase (if (e) then goto \ell' ):
b = evaluate\_concrete(e, \mathcal{M})
c = evaluate\_symbolic(e, \mathcal{M}, \mathcal{S})
if b then
   path\_constraint = path\_constraint ^ \langle c \rangle
    stack = compare\_and\_update\_stack(1, k, stack)
    \ell = \ell'
else
   path\_constraint = path\_constraint ^ \langle neg(c) \rangle
    stack = compare\_and\_update\_stack(0, k, stack)
    \ell = \ell + 1
k = k + 1
```

Update symbolic memory

Update concrete memory / PC

The instrumented program

```
ase (m \leftarrow e):
S = S + [m \mapsto evaluate\_symbolic(e, \mathcal{M}, S)]
v = evaluate\_concrete(e, \mathcal{M})
\mathcal{M} = \mathcal{M} + [m \mapsto v]; \ell = \ell + 1
ase (if (e) then goto \ell'):
b = evaluate\_concrete(e, \mathcal{M})
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    stack = compare\_and\_update\_stack(1, k, stack)
    \ell = \ell'
else
   path\_constraint = path\_constraint ^ \langle neg(c) \rangle
    stack = compare\_and\_update\_stack(0, k, stack)
    \ell = \ell + 1
k = k + 1
```

Record a list of all constraints taken to get to this conditional

Check to ensure that we're on the expected path and record if given conditionals are "done"

The stack

Kept as a record of execution so far

Stores two pieces of information for each conditional

- The branch taken (if = 1, else = 0)
- Whether the if and else branch have been explored (done)

Enables depth-first exploration of conditionals

Jpdating the stack

```
 \begin{array}{l} \textit{compare\_and\_update\_stack}(\textit{branch}, k, \textit{stack}) = \\ & \textbf{if } k < |\textit{stack}| \textbf{ then} \\ & \textbf{if } \textit{stack}[k].\textit{branch} \neq \textit{branch} \textbf{ then} \\ & \textit{forcing\_ok} = 0 \\ & \textbf{raise} \textbf{ an exception} \\ & \textbf{else if } k = |\textit{stack}| - 1 \textbf{ then} \\ & \textit{stack}[k].\textit{branch} = \textit{branch} \\ & \textit{stack}[k].\textit{done} = 1 \\ & \textbf{else } \textit{stack} = \textit{stack} \triangleq \langle (\textit{branch}, 0) \rangle \\ & \textbf{return } \textit{stack} \\ \end{array}
```

All other conditionals exception the one of interest should take the same branch as the previous execution

If we successfully reached the branch we were shooting for, that conditional is done

New conditionals are simply push on the top of the stack

Solving for new path

```
Find the first conditional has not been fully exploit j be the smallest number such that for all h with -1 \le j < h < k_{try}, stack[h]. done = 1 Find the first conditional has not been fully exploif j = -1 then return (0, \neg, \neg) // This directed search is over else path\_constraint[j] = neg(path\_constraint[j]) Flip the conditional to take the opposite branch stack[j].branch = \neg stack[j].branch if (path\_constraint[0, \dots, j] has a solution \vec{I} ) then return (1, stack[0..j], \vec{I} + \vec{I} ) else
```

solve_path_constraint(j,path_constraint,stack)

Overall Algorithm

```
run\_DART() =
  all_linear, all_locs_definite, forcing_ok = 1, 1, 1
   repeat
     stack = \langle \rangle; \vec{I} = []; directed = 1
     while (directed) do
        try (directed, stack, \vec{I}) =
            instrumented\_program(stack, \vec{I})
        catch any exception \rightarrow
           if (forcing_ok)
              print "Bug found"
              exit()
           else forcing_ok = 1
   until all\_linear \land all\_locs\_definite
```

Advantages over static analysis

Can function even when theorem solvers fail

_imitations

Incomplete in the presence of non-linear path constraints

- e.g., x*x
- all_linear = 0 -> DART will run forever

Library functions

- Can be explored via execution
- Can't be used to form path constraints; e.g., x = libFun(); if(x){} else {}

Results

Needham-Schoeder Protocol

- Protocol for handshake
- Has a known security vulnerability (man in the middle)

oSIP

- Was able to crash 65% of the external functions
- Most of these turned out to be due to non-uniform handling of NULL
- Found a security vulnerability that caused the parser to crash

Discussion

Their results on real oSIP aren't very motivating

- Most of the errors are null pointers
- How successful would DART be on coreutils?

Can DART be applied to incremental codes changes?