Coverage-based Greybox Fuzzing as Markov Chain

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Some of the slides are adapted from Author's presentation.

Introduction

Fuzz testing is an automated testing technique that uncovers software error by executing the target program with large number of *randomly* generated test inputs.

Three main approaches.

- Black-box fuzzing : Random testing[1].
- White-box fuzzing: SAGE [2].
- Grey-box fuzzing : American Fuzzy Lop [3].

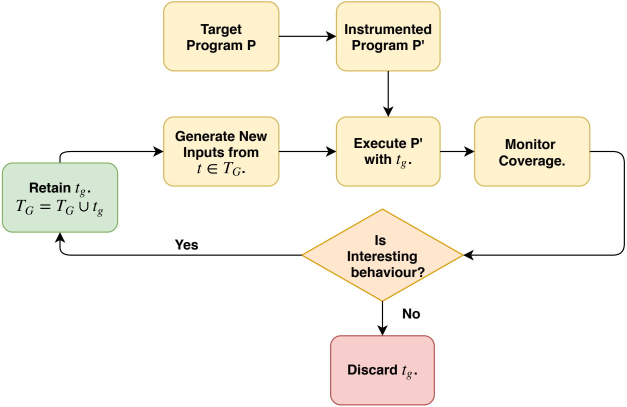
[1] Miller et al, An empirical study of Unix utilities, CACM, 1990.

[2] Goefroid et al, Automated whitebox fuzz testing, NDSS, 2008.

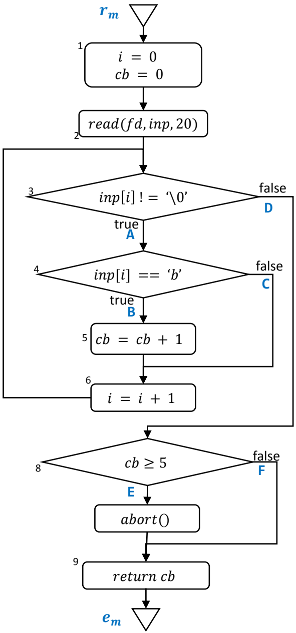
[3] Zalewski, http://lcamtuf.coredump.cx/afl/.

Grey-box fuzzing

Black-Box Fuzzing $\rightarrow$ Open Loop Control System.
GreyBox Fuzzing $\rightarrow$ Closed Loop Control System.
Feedback Function H(s) $\sim$ Branch-Pair Coverage (Pair of consecutive nodes in a CFG)



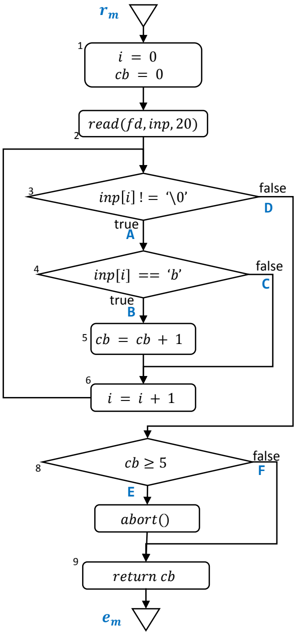
Grey-box fuzzing – Working example

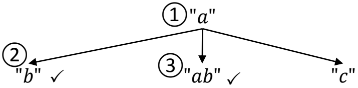


1 "a"

Id	input	AB	AC	BA	CA	BD	CD	DE	DF
1	"a"		1				1		1

Grey-box fuzzing – Working example





Id	input	AB	AC	BA	CA	BD	CD	DE	DF
1	"a"		1				1		1
2	“b”	1				1			1
3	“ab”	1	1		1	1			1
	“c”		1				1		1

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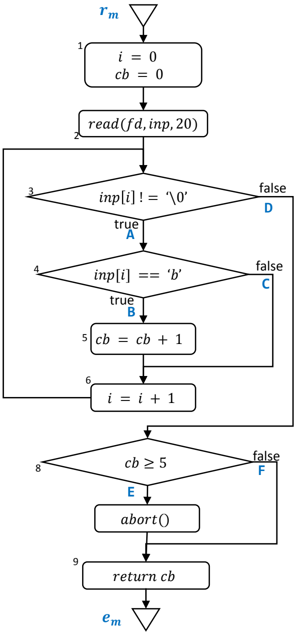

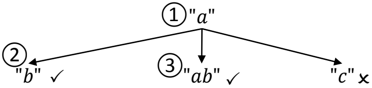

Id	input	AB	AC	BA	CA	BD	CD	DE	DF
1	"a"		1				1		1
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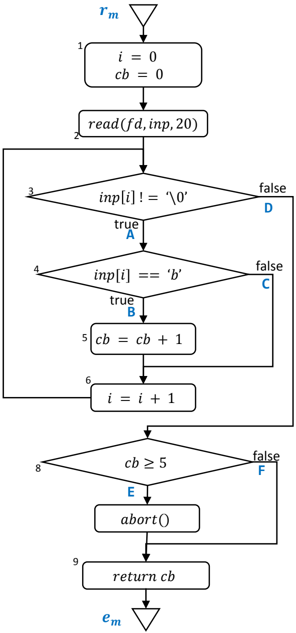

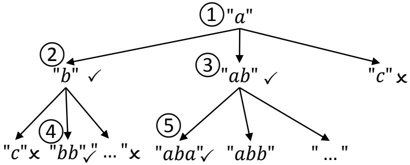

Id	input	AB	AC	BA	CA	BD	CD	DE	DF
1	"a"		1				1		1
2	"b"	1				1			1
3	"ab"	1	1		1	1			1
4	"bb"	2		1		1			1
5	"aba"	1	2	1	1		1		1
	"abb"	2	1	1	1	1			1

Grey-box fuzzing algorithm

Algorithm 1 Grey-box fuzzing algorithm

Require: Program P, Initial non-crashing seeds I_s.
Ensure: Set of crashing inputs T_C and a tree of test inputs T_G for P.

$T_G = I_s$
Run P with I_s and observe visit counts of *branch pairs*.
repeat
  t = getNextInput() ▷ $t \in T_G$.
  N = assignEnergy(t)
  T_m = fuzzTestInput(t,N) ▷ $T_m : \{t_g | t_g \in MUTATE(t)\}$
  for all $t_g \in T_m$ **do**
    S_g = run(P,t_g)
    if $S_g = \perp$ **then** ▷ Did t_g caused a crash or hang ?
      $T_C.add(t_g)$
    else if isInterestingTestInput(t_g,S_g) **then**
      $T_G.add(t_g)$ ▷ Retain interesting test input
    end if
  end for
until User interrupt received.
return (T_G, T_C)

$N = assignEnergy(t)$

Let N=100.

Let N_1 be the $N * a$ factor inversely proportional to t_g's execution time.

(Ranging from 0.1 for higher execution time to 3 times for lower execution times)

Let N_2 be $N_1 * a$ factor based on number of branch pairs covered by t_g.

(Ranging from 0.25 for lower coverage to 3 times for higher coverage)

Let N_3 be $N_2 * a$ factor based on cycle of t_g's discovery and number of time t fuzzed.

(Low = 1 to high = 4)

Let N_4 be $N_3 * a$ factor based on depth of t_g's discovery.

(Low = 1 to high = 5)

return N_4

Problem Statement

```
void crashme (char *s) {

  if(s[0] == 'b')

    if(s[1] == 'a')

      if(s[2] == 'd')

        if(s[3] == '!')

            abort() ;
}
```

Listing 1: Program crashes when string s == "bad!"

BlackBox Fuzzing

- Assumption : 2^8 characters.
- Expected no. of testcase required to catch the bug : 2^{32}.

Coverage-based GreyBox Fuzzing (CGF)

- Markov Chain modeling of CGF gives the expectation that 2^{12} is minimum test required to catch the crash.
- Current CGF algorithms are independent of judicious energy assignment to interesting test vectors for further fuzzing.

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      if(s[2] == 'd')

        if(s[3] == '!')

          abort() ;
}
```

Listing 2: Program crashes when string s == "bad!"

Objective

Tune energy assignment scheme close to ideal.

BlackBox Fuzzing

- Assumption : 2^8 characters.
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Coverage-based GreyBox Fuzzing (CGF)

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Some terminologies

Branch Pair Tuple BP_i : $<bp_i, C_i>$ where, bp_i - Branch Pair i, C_i - Visit Count.

Path: Sequence of branch pair tuples $[BP_i, BP_j \ldots]$ visited during the execution of the program P on a test vector t.

Basic Concepts : Probabilistic Modeling

Random Variable

Maps possible outcomes from Sample Space to a real valued number.

$$X : \Omega \rightarrow \mathbb{R}$$

Conditional Probability

Calculates probability of an event happening, given a partial information.

$$P(B|A) = P(B \cap A)/P(A)$$

Stochastic Process

Collection of Random Variables indexed by time.

Discrete Time Stochastic Process (DTSP)

Sequence of random variables X_0, X_1, X_2, . . Denoted by $\{ X_n \}$.

Time: n = 0, 1, 2, . . .

State Space: m-dimensional vector, s = $(s_1, s_2, \ldots, s_m)$
Set of all values that the X_n's can take.

Also, X_n takes one of m values, so $X_n \leftrightarrow s$.

Discrete Time Markov Chain (DTMC)

DTSP $\rightarrow$ Discrete time Markov Chain (DTMC) iff

$P[X_{n+1} = j \mid X_n = i_n, ..., X_0 = i_0] = P[X_{n+1} = j \mid X_n = i_n] = P_{ij}(n)$ (Markovian Property)

Markov Property

Future state is independent of the past given the present state is fully known/observable.

$P_{ij}(n)$: Probability of transition from state i to state j, at time n.

This is also referred as one-step transition probability.

Rat Maze Problem as DTMC

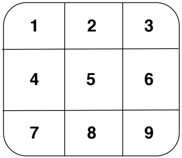


Figure : A rat maze. Allowed transitions are horizontal and vertical neighbors.

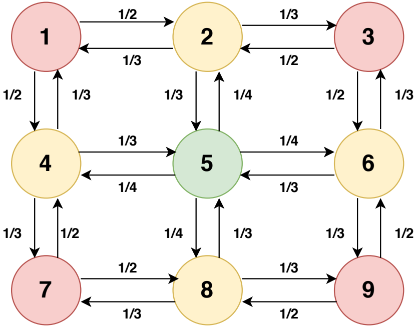


Figure : Markov Chain Modeling of Rat Maze Problem

Homogeneous DTMC

DTMC $\rightarrow$ Homogeneous iff transition probabilities do not depend on the time n, i.e.

$P[X_{n+1} = j | Xn = i] = P[X_1 = j | X_0 = i] = P_{ij}$.

Transition matrix of Homogeneous DTMC $P = [P_{ij}]_{i,j \in E}$

$$P = \begin{pmatrix} p_{1,1} & p_{1,2} & p_{1,3} & p_{1,4} \\ p_{2,1} & p_{2,2} & p_{2,3} & p_{2,4} \\ p_{3,1} & p_{3,2} & p_{3,3} & p_{3,4} \\ p_{4,1} & p_{4,2} & p_{4,3} & p_{4,4} \end{pmatrix}$$

Coverage-Based Fuzzing as Homogeneous DTMC

Coverage-based Greybox fuzzing can modeled as Timed homogeneous DTMC.

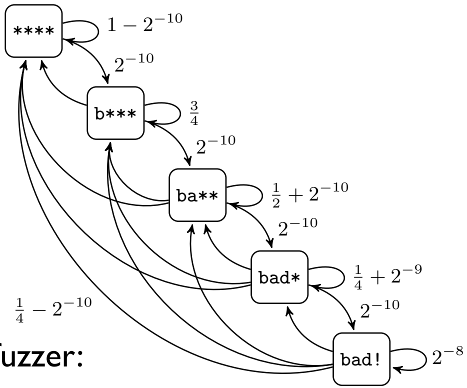
State Space $S = S^+ + S^-$.

S^+ - Paths already explored by seeds T_G.
S^- - Paths yet to be discovered by fuzzing $t \in T_G$.

Assumptions :
Probability of exercising path i(undiscovered) from already generated input t_j, is same as probability of creating test input t_j from test vectors t_i.

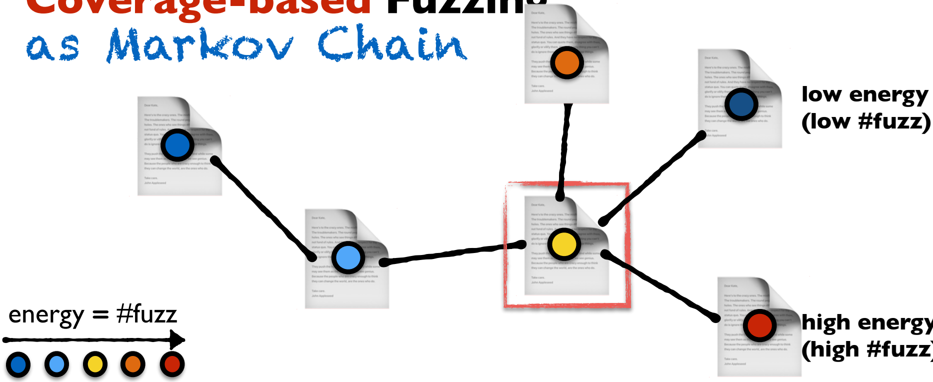
Example

```
void crashme (char* s) {
  if (s[0] == 'b')
    if (s[1] == 'a')
      if (s[2] == 'd')
        if (s[3] == '!')
          abort();
}
```



- Defining the coverage-based fuzzer:
  - Start with seed that is a random 4-letter word.
  - Given a seed, the fuzzer chooses a letter and substitutes it.

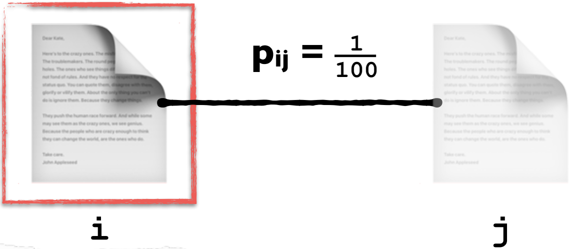
Greybox Coverage-based Fuzzing as Markov Chain



Markov chain describes the probability $\mathtt{p_{ij}}$ that fuzzing the input exercising path $\mathtt{i}$ generates an input exercising path $\mathtt{j}$

Coverage-based Fuzzing as Markov Chain

Greybox



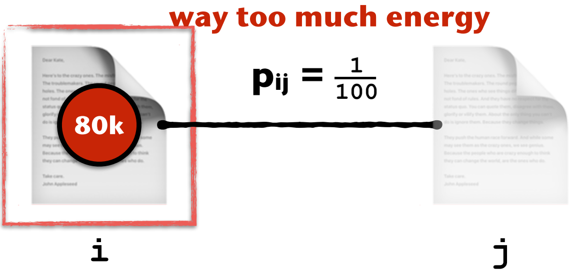
$$p_{ij} = \frac{1}{100}$$

= What is the minimum energy required to expect discovery of new path j?

Greybox

Challenges of Coverage-based Fuzzing

- AFL's power schedule is *constant* in the number of times s(i) the seed has been chosen for fuzzing.



Greybox

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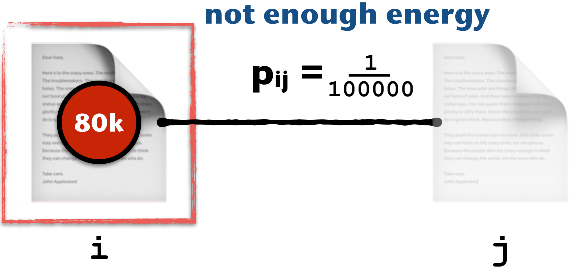
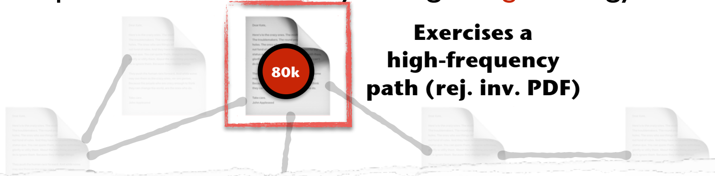


Greybox

Challenges of **Coverage-based** Fuzzing

- AFL's power schedule is *constant* in the number of times s(i) the seed has been chosen for fuzzing.
- AFL's power schedule always assigns *high* energy



Too much energy assigned to high-frequency paths!

Stationary Distribution and Neighborhood Density

For a time homogeneous DTMC, the vector π is called stationary distribution of MC.

$$\forall j \in S,\ 0 \leq \pi_j \leq 1.$$
$$1 = \sum_{i \in S} \pi_i.$$
$$\pi_j = \sum_{i \in S} \pi_i * p_{ij}$$

Neighborhood Density of π

- High Density Region :- Set of neighborhood of paths I , where $\mu_{i \in I}(\pi_i) > \mu_{t_g \in T_G}(\pi_g)$.
- Low Density Region :- Set of neighborhood of paths I , where $\mu_{i \in I}(\pi_i) < \mu_{t_g \in T_G}(\pi_g)$.

μ : Arithmetic Mean

Greybox

Challenges of Coverage-based Fuzzing

- AFL spends too much energy on high-frequency paths.
- We suggest to spend more energy on low-frequency paths and less energy on high-frequency paths.
- We suggest to spend the minimum energy required to discover a new state.

A power schedule manages the energy spent on each state.

Power Schedules

- Constant: $p(i) = \alpha(i)$
  - AFL uses this schedule (fuzzing ~1 minute)
  - $\alpha(i)$ .. how AFL judges fuzzing time for the test exercising path i
- Cut-off Exponential: $p(i) = \begin{cases} 0 & \text{if } f(i) > \mu \\ \min\left(\frac{\alpha(i)}{\beta} \cdot 2^{s(i)}, M\right) & \text{otherwise.} \end{cases}$
  - energy increases exponentially
  - but spend no energy on states in high-density region
  - $\beta > 1$ .. is a constant
  - $s(i)$ .. #times the input exercising path i has been chosen for fuzzing
  - $f(i)$ .. #fuzz exercising path i (path-frequency)
  - μ .. mean #fuzz exercising a discovered path (avg. path-frequency)
  - M .. maximum energy expendable on a state

Power Schedules

- Exponential: $p(i) = \min\left(\frac{\alpha(i)}{\beta} \cdot \frac{2^{s(i)}}{f(i)}, M\right)$
  - Instead of spending *no* energy on states in high-density region,
  - spend energy *proportional* to the density for the state's region
- Cut-off Exponential: $p(i) = \begin{cases} 0 & \text{if } f(i) > \mu \\ \min\left(\frac{\alpha(i)}{\beta} \cdot 2^{s(i)}, M\right) & \text{otherwise.} \end{cases}$
  - energy increases exponentially
  - but spend no energy on states in high-density region

  - $\beta > 1$ .. is a constant
  - $s(i)$ .. #times the input exercising path i has been chosen for fuzzing
  - $f(i)$ .. #fuzz exercising path i (approx. the page rank of i)
  - μ .. mean #fuzz exercising a discovered path
  - M .. maximum energy expendable on a state

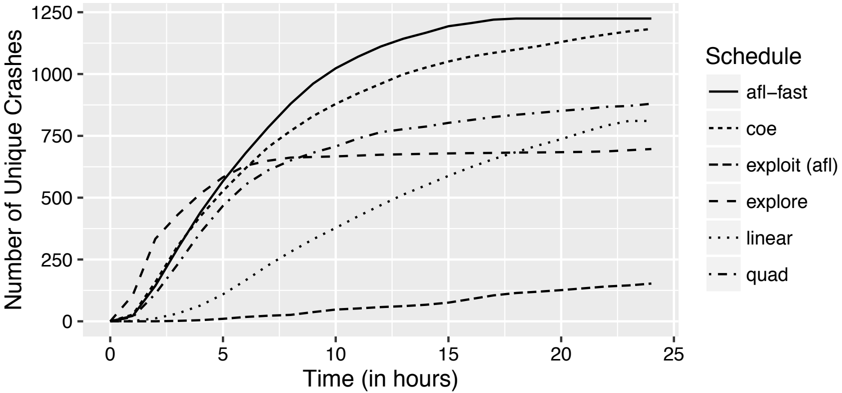
Experiments

- Binutils (nm, objdump, strings, size, cxxfilt)
  - it is a difficult subject because it takes program binaries as input.
  - vulnerabilities exist in GDB, Valgrind, Gcov and other libbfd-based tools.
  - attacker might modify a binary such that it becomes malicious upon analysis!
    - e.g., during *scan* for malicious software or during reverse engineering.

Vulnerability	Type
CVE-2016-2226	Exploitable Buffer Overflow
CVE-2016-4487	Invalid Write due to a Use-After-Free
CVE-2016-4488	Invalid Write due to a Use-After-Free
CVE-2016-4489	Invalid Write due to Integer Overflow
CVE-2016-4490	Write Access Violation
CVE-2016-4491	Various Stack Corruptions
CVE-2016-4492	Write Access Violation
CVE-2016-4493	Write Access Violation
CVE Requested	Stack Corruption
Bug 1	Buffer Overflow (Invalid Read)
Bug 2	Buffer Overflow (Invalid Read)
Bug 3	Buffer Overflow (Invalid Read)

We found and reported these vulns. AND use them for our evaluation.

Power Schedules



AFLFast @ DARPA Cyber Grand Challenge

- An independent evaluation by team Codejitsu found that AFLFast exposes errors in the benchmark binaries of the DARPA Cyber Grand Challenge 19x faster than AFL.
- In the CGC finals, team Codejitsu placed 5th overall but placed 2nd in terms of Vulnerability Detection (i.e., 2nd highest evaluation score).

Questions ?

Thank You !