Lecture 2 – Random Testing

AAA705: Software Testing and Quality Assurance

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PLRG

2024 Spring

Recall

- Equivalence Partitioning (EP)
- Boundary Value Analysis (BVA)
- Category Partition Method (CPM)
- Combinatorial Testing (CT)
  - Covering Array (CA)
  - Fault Detection Effectiveness
  - Greedy Algorithm – IPOG Strategy
  - Greedy vs. Meta-heuristic

Contents

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Random Testing

- We need to **sample** the test input from the vast and possibly infinite **input space**.

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  - Since developers has their own mental model of the software, they often have a **biased** view of the input space.

  - **Random testing** can help to ignore this bias.

Random Testing

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Random Testing

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- F: a subset of S – a set of all failing test inputs

Random Testing

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$$\text{Failure Rate } t = \frac{|F|}{|S|}$$

(The probability that a randomly sampled test input is fail when we sample uniformly at random from S)

Random Testing – Example

```c
/* C */
int abs(int x) {
  if (x < 0) return x;      // should be -x
  else return x;
}
```

- Failure Rate $t \approx 0.5$
- Oracle
  - `assertEqual(abs(-5), 5)`
  - `assertEqual(abs(5), 5)`

How Random Can We Get?

- **Pseudo-random number generators (PRNGs)**

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  - **Xorshift** – Fast but fail some tests / variants (xorshift+, xoshiro, etc.)
- **True-random number generators** (TRNGs) – expensive
  - **Atmospheric noise** – https://random.org
  - **Quantum random number generator (QRNG)** – https://qrng.anu.edu.au
  - **Lava lamps** – **Cloudflare**

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How Random Can We Get?

The new Galaxy Quantum 4 is equipped with the world's smallest (width 2.5mm x length 2.5mm) **Quantum Random Number Generator (QRNG)** chipset, enabling trusted authentication and encryption of information.

Probabilistic Analysis

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- Given n random test inputs, what is the **probability** of finding **at least one failure**?

Probabilistic Analysis – Geometric Distribution

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- The **probability mass function (PMF)** of the geometric distribution:

$$Pr(X = k) = (1 - p)^{k-1} p$$

It is the probability that the first success occurs on the n-th trial.

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Probabilistic Analysis – Geometric Distribution

- Given a failure rate p, **how many** test inputs do we need to sample to find the **first failure**?
- **Mean** (If p = 0.01, the average test inputs = 100)

$$\frac{1}{p}$$

- **Median** (If p = 0.01, the median test inputs ≈ 69)

$$\left\lceil \frac{-1}{\log_2(1-p)} \right\rceil$$

- **Variance** (If p = 0.01, the variance = 9900)

$$\frac{1-p}{p^2}$$

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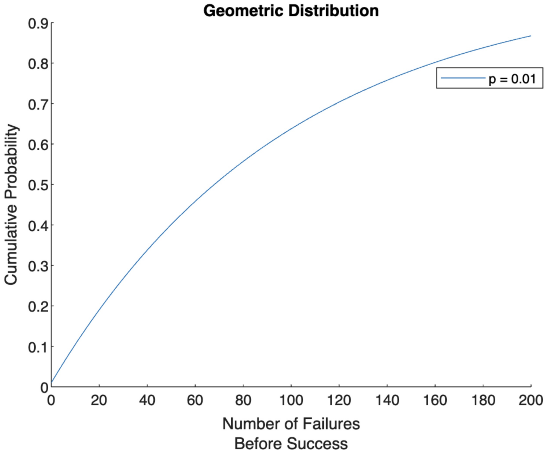
Probabilistic Analysis – Geometric Distribution

- If we test $n = 100$ random test inputs, the probability of finding at least one failure is $1 - (1 - 0.01)^{101} = 63.76\%$.
- If we test $n = 200$ random test inputs, the probability of finding at least one failure is $1 - (1 - 0.01)^{201} = 86.74\%$.



Probabilistic Analysis – Geometric Distribution

- Unfortunately, failure rate p is **unknown** in practice.
- But, we can **estimate** p in various ways:
  - Previous versions of the software
  - Similar software
  - Literature

Weakness of Random Testing

- Random testing provides **no guidance**; it is the **needle in a haystack** problem – the probability of finding a failure is low.

```c
/* C */
void foo(int x) {
  if (x == 0) {
    /* faulty code here */
  }
}
```

```python
# Python
def foo(x):
  # e.g., x = 2840
  if (x * 7919 % 5711 == 42):
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- We need **biased** random testing with predefined probability:
  - **Special values** (-0, `null`, π, ...)
  - **Extracted values** from code (e.g., constants, literals)
  - **Previously successful values**

Examples

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- **Google** (2006) - "DiRT"' for Site Reliability Engineering (SRE)

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- **Netflix** (2011) – **“Chaos Monkey”** that randomly terminates AWS instances to test the fault tolerance of the Netflix infrastructure.

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- **Without knowing** the faulty regions, what is the **best way** to sample the test inputs?

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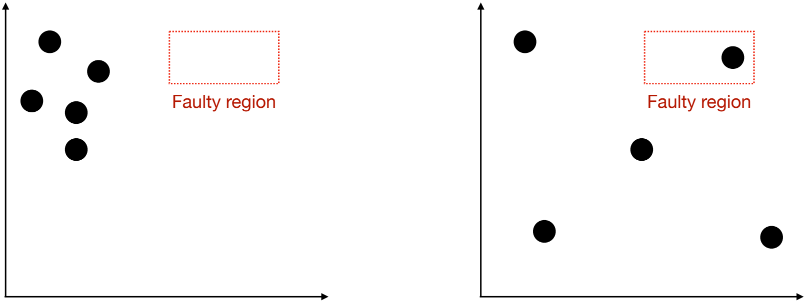

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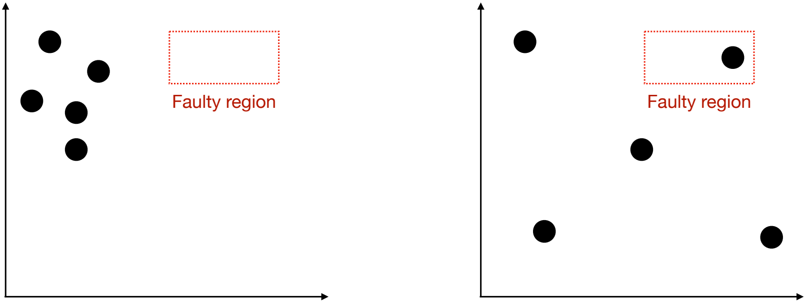

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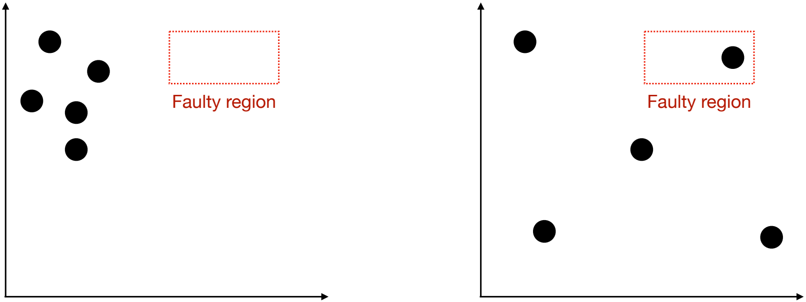

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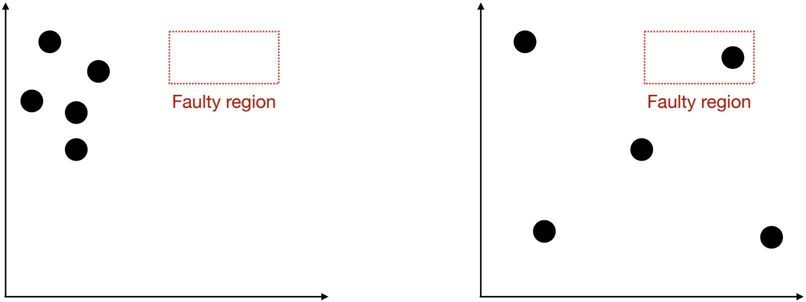

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- Then, how to measure the distance between **complex data types**?

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- and the distance between "uninformed" and "uniform" is 3:

$$\text{“uninformed”} \xrightarrow[n]{\text{delete}} \text{“uniformed”} \xrightarrow[e]{\text{delete}} \text{“uniformd”} \xrightarrow[d]{\text{delete}} \text{“uniform”}$$

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- The formal definition of the **Levenshtein distance** is as follows:

$$
lev(a, b) = \begin{cases} |a| & \text{if } |b| = 0 \\ |b| & \text{if } |a| = 0 \\ lev(tail(a), tail(b)) & \text{if } head(a) = head(b) \\ 1 + \min \begin{cases} lev(tail(a), b) & \text{(insert)} \\ lev(a, tail(b)) & \text{(delete)} \\ lev(tail(a), tail(b)) & \text{(substitute)} \end{cases} & \text{otherwise} \end{cases}
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- It is usually extended into a parameterized version with a set of allowed **edit operations** (e.g., transposition) with different **costs**.
- **Wagner-Fischer algorithm** (1967) – $O(mn)$ time complexity
- Indyk and Bačkurs (2015) proved that the problem of finding the edit distance **cannot be solved in less than quadratic time**. (We cannot do better than the Wagner-Fischer algorithm.)

Adaptive Random Testing (ART)

- The **diversity** of a test suite is defined as the **sum of distances** between all pairs of test inputs.

$$
\mathit{diversity}(T) = \sum_{(t_1, t_2) \in T \times T} d(t_1, t_2)
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- Choose the test input that has the **maximum** distance from the existing test inputs.
- Add the **chosen new test input** to the set of existing test inputs.
- Iterate the process until the **stopping criterion** is met.

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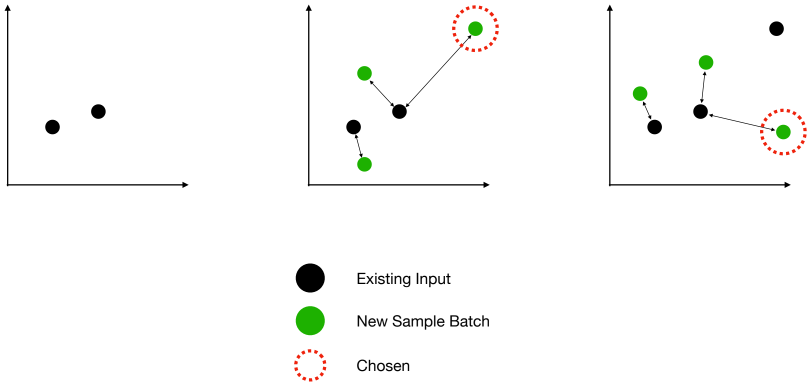

- It **samples** $Z = 3$ new test inputs and **chooses** the one with the **maximum distance** from the existing test inputs.

Distance Comparison Target

- For each **new test case** t, we need to choose the **target for comparison** in the existing test suite T.[3]

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$$fitness(t, T) = \frac{1}{|T|} \sum_{t' \in T} d(t, t')$$

- Maximum-Distance

$$fitness(t, T) = \max_{t' \in T} d(t, t')$$

- Centroid-Distance

$$fitness(t, T) = d(t, 1/|T| \sum_{t' \in T} t')$$

[3] **[CSUR'19]** R. Huang et al. *"A survey on adaptive random testing."*

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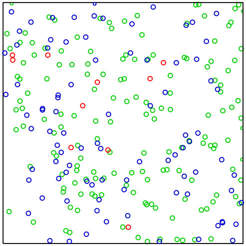
- It may be difficult to choose the meaningful **distance metric** for complex data types.

Quasi-Random Strategy for ART



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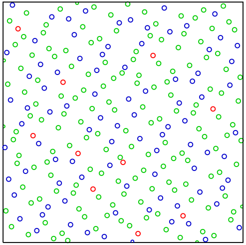

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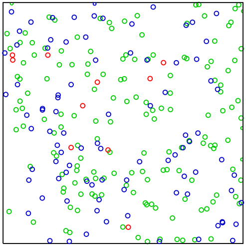

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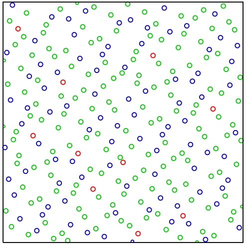

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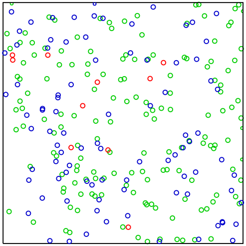

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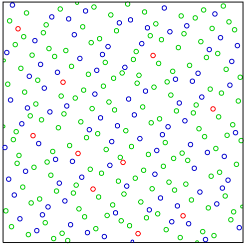

- What if we can randomly sample the test inputs having **diversity** (i.e., **low discrepancy**)?
- **Quasi-random** sequences could be a good choice.
- Let's learn **Halton sequence**, one of the representative quasi-random sequences.

Quasi-Random Strategy for ART – Halton Sequence

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PLRG

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\begin{array}{llll}
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\frac{1}{8} & \frac{5}{8} & \frac{3}{8} & \frac{7}{8} \\
\frac{1}{16} & \cdots & &
\end{array}
$$

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- Generate a sequence of pairs of numbers (x, y) by combining above sequences.

$$(\frac{1}{2}, \frac{1}{3}), (\frac{1}{4}, \frac{2}{3}), (\frac{3}{4}, \frac{1}{9}), (\frac{1}{8}, \frac{4}{9}), (\frac{5}{8}, \frac{7}{9}), (\frac{3}{8}, \frac{2}{9}), (\frac{7}{8}, \frac{5}{9}), (\frac{1}{16}, \frac{8}{9}), \dots$$

Quasi-Random Strategy for ART

We can utilize other quasi-random sequences for ART:[4]

- Halton Sequence

$$\phi_b(i) = \sum_{j=0}^{\omega} i_j b^{-j-1}$$

- Sobol Sequence

$$Sobol(i) = XOR_{j=1,2,\cdots,\omega}(i_j \delta_j)$$

where

$$\delta_j = XOR_{k=1,2,\cdots,r}\left(\frac{\beta_k \delta_{j-k}}{2^j}\right) \oplus \frac{\delta_{j-k}}{2^{j+r}}$$

- Niederreiter Sequence

[4] **[CSUR'19]** R. Huang et al. *"A survey on adaptive random testing."*

Adaptive Random Testing (ART) – Summary

- **Application Domains**
  - Numeric Programs
  - Object-Oriented Programs
  - Configurable Systems
  - Web Services and Applications
  - Embedded Systems
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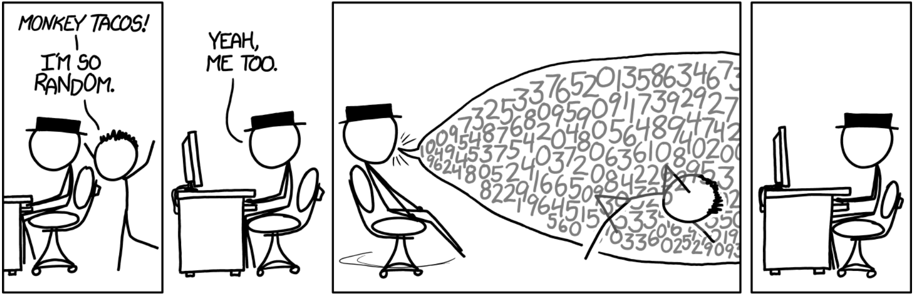
- **Faulty regions** may not apply to all types of faults.
- **ART** is still mostly an academic idea, with debates going on:
  - **[ISSTA'11]** A. Arcuri et al. *"Adaptive random testing: an illusion of effectiveness?"*
  - **[CSUR'19]** R. Huang et al. *"A survey on adaptive random testing."*

Contents

Fuzz Testing



https://xkcd.com/1210/

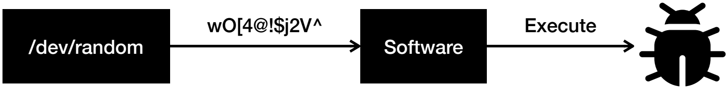
Fuzz Testing

- **[CACM'90]** B. P. Miller et al. *"An empirical study of the reliability of UNIX utilities."*[5]

"On a dark and stormy night one of the authors was logged on to his workstation on a dial-up line from home and the **rain** *had affected the phone lines; there were* **frequent spurious characters** *on the line. The author had to race to see if he could type a sensible sequence of characters before the noise scrambled the command. This line noise was not surprising; but we were surprised that these* **spurious characters were causing programs to crash***."*

[5] https://alastairreid.github.io/RelatedWork/papers/miller:cacm:1990/

Fuzz Testing



- **Fuzz testing** is a random testing technique to find **exceptional outcomes** (e.g., crashes, exceptions, freezes, etc.) of a software system.

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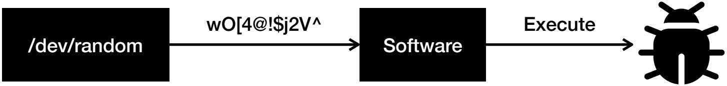

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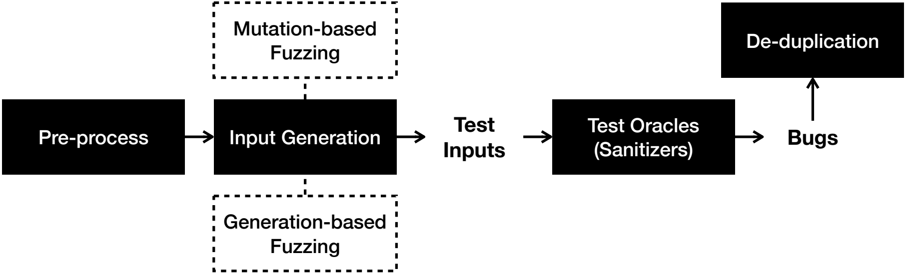
- 1990 study found crashes in: `adb`, `as`, `bc`, `cb`, `col`, `diction`, `emacs`, `eqn`, `ftp`, `indent`, `lex`, `look`, `m4`, `make`, `nroff`, `plot`, `prolog`, `ptx`, `refer!`, `spell`, `style`, `tsort`, `uniq`, `vgrind`, `vi`

Fuzz Testing – Overview



- **Pre-process** – prepare the SUT for fuzz testing
- **Input Generation** – generate test inputs
  - **Mutation-Based Fuzzing** – modify existing test inputs
  - **Generation-Based Fuzzing** – generate new test inputs
- **Test Oracles (Sanitizers)** – detect exceptional outcomes
- **De-duplication** – remove duplicate test inputs

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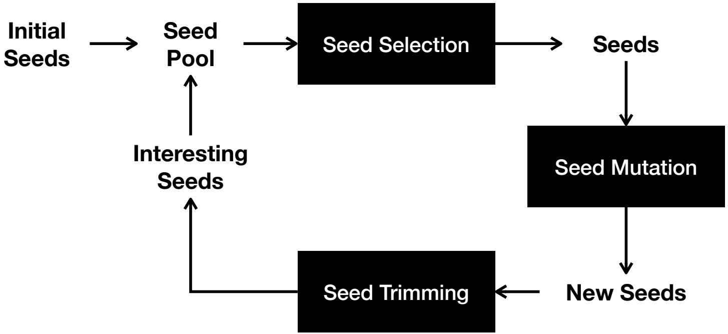
  - **Libraries** – a driver program that calls functions in the library
  - **Kernels** – may fuzz user-land applications to test kernels
  - **IoT devices** – a driver communicate with the corresponding smartphone application.

Input Generation – Mutation-Based Fuzzing



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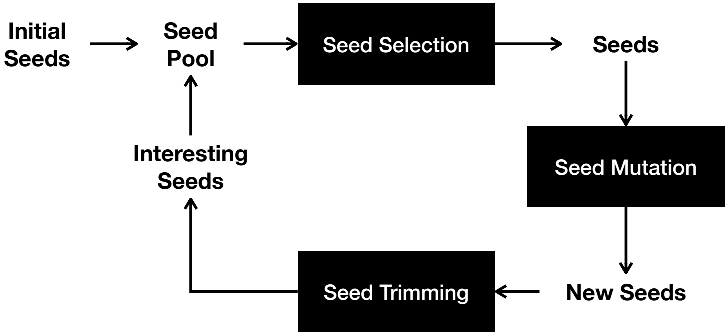

- In the mutation-based fuzzing, a **seed** is a test input that is used to generate new test inputs.
- **Mutation-Based Fuzzing** first initializes **seed pool** with the initial seeds, and then **mutates** them to generate new test inputs and **updates** the seed pool when a new test input is interesting.

Input Generation – Mutation-Based Fuzzing

- **Initial Seeds** – from the **existing test suite**, **manually crafted**, **inferred** from the SUT or specification.

[6] **[ICSE'21]** J. Park et al. *"JEST: N+1-version Differential Testing of Both JavaScript Engines and Specification."*

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- **Encoder Model** – generates test inputs for **decoder programs** (e.g., image decoders, audio decoders, etc.) using the corresponding **encoder programs**.

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- They are usually **instrumented** into the SUT to collect information about the execution in compile time (**static**) or runtime (**dynamic**) with **runtime overhead**.

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foo	x
bar	y
g	g
h	h
foo (crashed)	foo (crashed)

(e.g., both are the same with the stack backtrace hashing with $n = 3$)

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  - **Stack Backtrace Hashing –** hash the (limited) **stack backtrace** of the exceptional outcome and compare the **hash values**

foo	x
bar	y
g	g
h	h
foo (crashed)	foo (crashed)

(e.g., both are the same with the stack backtrace hashing with $n = 3$)

  - **Coverage-based De-duplication –** compare the **coverage** of the test inputs (e.g., node, branch, grammar, semantics, etc.)

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  - **Coverage-based De-duplication** – compare the **coverage** of the test inputs (e.g., node, branch, grammar, semantics, etc.)
  - **Semantic-aware De-duplication** – compare the **semantics** of the test inputs (e.g., **backward data-flow analysis** for blaming)

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- **ClusterFuzz** developed by Google

  https://google.github.io/clusterfuzz

Summary

1. Random Testing (RT)
   - Probabilistic Analysis
   - Weaknesses of Random Testing
   - Examples
2. Adaptive Random Testing (ART)
   - Levenshtein (Edit) Distance
   - Distance Comparison Target
   - Complexity of ART
   - Quasi-Random Strategy for ART
3. Fuzz Testing
   - Pre-process
   - Input Generation – Mutation-Based Fuzzing
   - Input Generation – Generation-Based Fuzzing
   - Test Oracles (Sanitizers)
   - De-duplication

Next Lecture

- Coverage Criteria

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