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Lecture 13: Automated Test Case Generation

Gregory Gay

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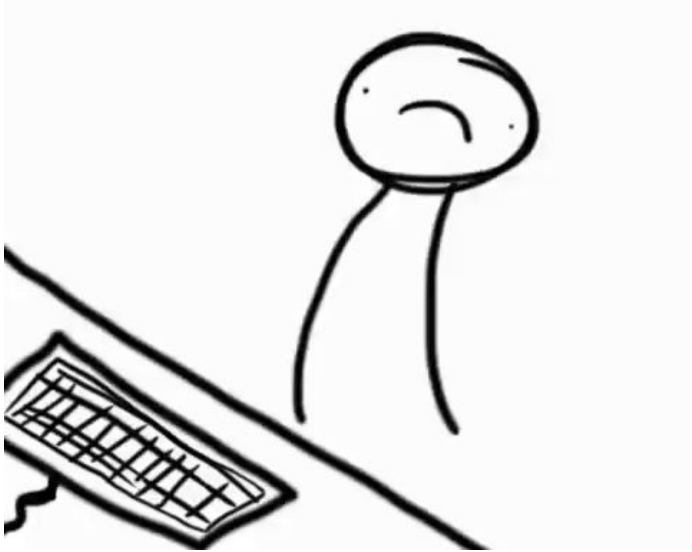
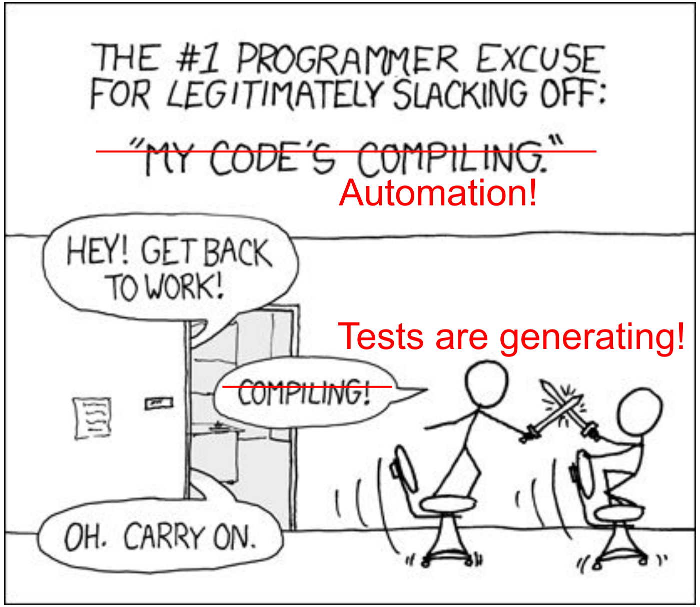
Automating Test Creation

- Testing is invaluable, but expensive.
  - We test for ***many*** purposes.
  - Near-infinite number of possible tests we could try.
  - Hard to achieve meaningful volume.



Automation of Test Creation

- Relieve cost by automating test creation.
  - Repetitive tasks that do not **need** human attention.
  - **Generate test input**.
    - Need to add assertions.
    - Or just look for crashes.



Today's Goals

- Introduce Search-Based Test Generation (Fuzzing)
  - Test Creation as a Search Problem
  - Metaheuristic Search
  - Fitness Functions
- Example - Generating Covering Arrays for Combinatorial Interaction Testing

Test Creation as a Search Problem

- Do you have a **goal** in mind when testing?
  - *Make the program crash, achieve code coverage, cover all 2-way interactions, …*
- You are **searching** for a test suite that achieves that goal.
  - Algorithm samples possible test input to find those tests.

Test Creation as a Search Problem

- “I want to find all faults” cannot be measured.
- *However, a lot of testing goals can be.*
  - Check whether properties satisfied (boolean)
  - Measure code coverage (%)
  - Count the number of crashes or exceptions thrown (#)
- If goal can be measured, search can be automated.

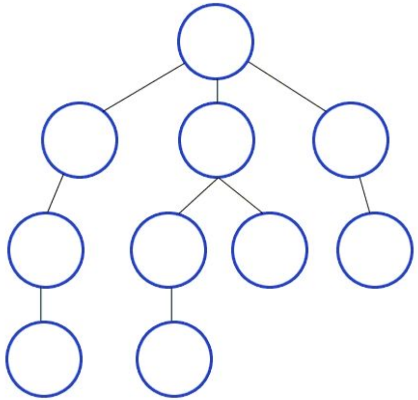
Search-Based Test Generation

- **Make one or more guesses.**
  - Generate one or more individual test cases or full suites.
- **Check whether goal is met.**
  - Score each guess.
- **Try until time runs out.**
  - Alter the population based on strategy and try again!

Search Strategy

- The order that solutions are tried is the key to efficiently finding a solution.
- A search follows some defined strategy.
  - Called a “**heuristic**”.
- Heuristics are used to choose solutions and to ignore solutions known to be unviable.
  - Smarter than pure random guessing!

Heuristics - Graph Search



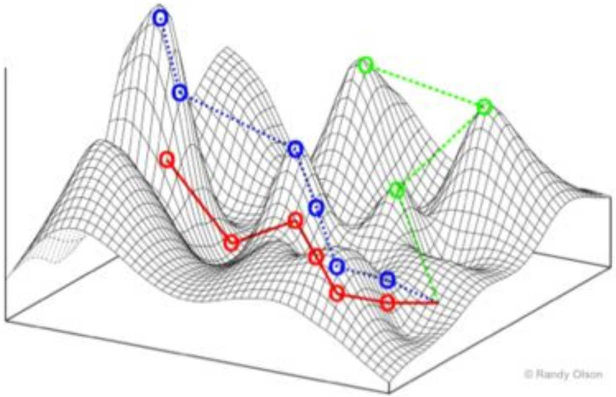
- Arrange nodes into a hierarchy.
  - Breadth-first search looks at all nodes on the same level.
  - Depth-first search drops down hierarchy until backtracking must occur.
- Attempt to estimate shortest path.
  - A* search examines distance traveled and estimates optimal next step.
  - Requires domain-specific scoring function.

How Long Do We Spend Searching?

- Exhaustive search not viable.
- Search can be bound by a **search budget**.
  - Number of guesses.
  - Time allotted to the search (number of minutes/seconds).
- **Optimization problem**:
  - *Best solution possible before running out of budget.*

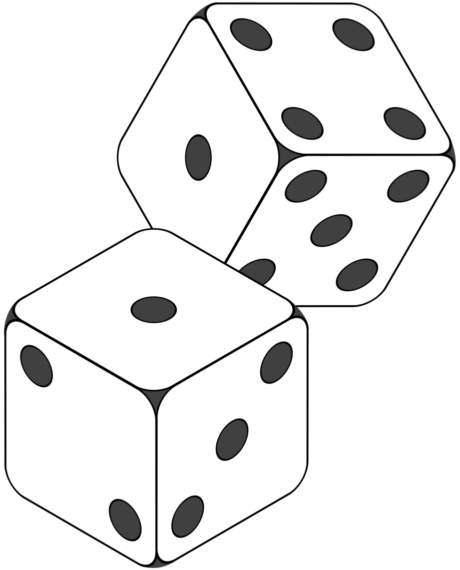
Generation as Optimization Problem

- Search heuristic becomes important.
  - If time bound: time to create, execute, and evaluate.
  - If attempt bound: strategy used to choose next solution.
    - Ignoring bad solutions, learning what a solution good.
  - In practice, **efficiency in both categories is desired**.



Random Search

- Randomly formulate a solution.
    - Unit testing: choose a class in the system, choose random methods, call with random parameter values.
    - System-level testing: choose an interface, choose random functions from interface, call with random values.
- Keep trying until goal attained or budget expires.

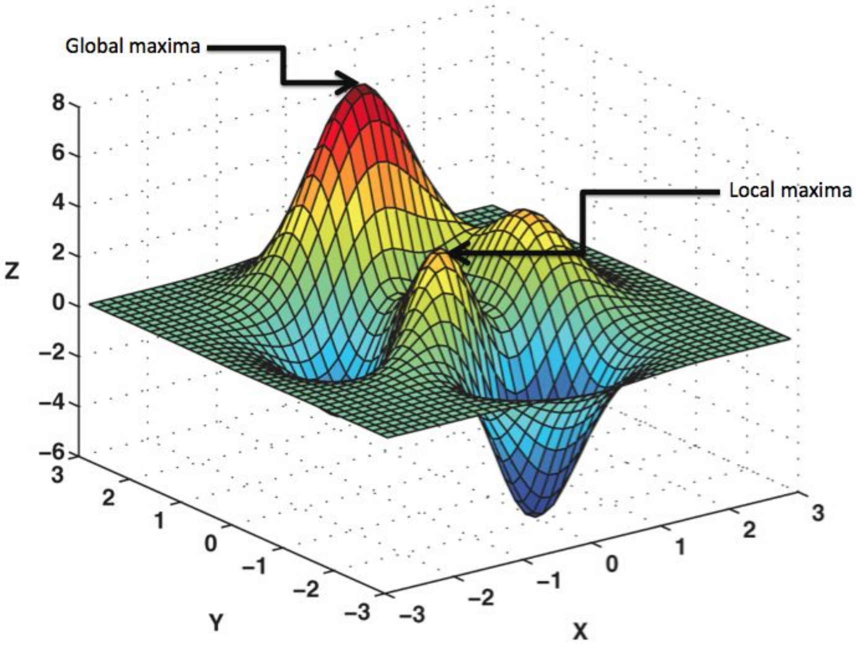


Random Search

- Sometime viable:
  - Extremely fast.
  - Easy to implement, easy to understand.
  - All inputs considered equal, so no designer bias.
- However…

Metaheuristic Search

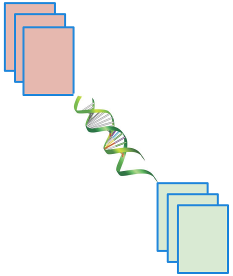
- Random search is naive.
  - Only possible to cover a small % of full input space.
- Metaheuristic search adds intelligence to random.
  - Feedback and sampling strategies.
  - Still fast, able to learn from bad guesses.



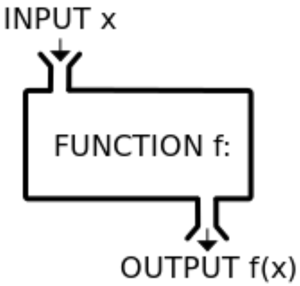
Metaheuristic Search

Mechanics of Optimization

AKA: How can I get a computer to search?

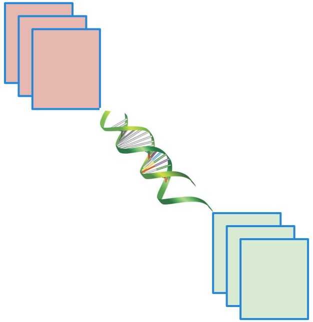


Metaheuristic



Fitness Function(s)

Search-Based Test Generation



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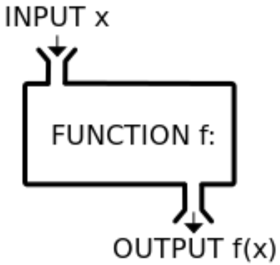

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The Metaheuristic (Sampling Strategy)

Genetic Algorithm
Simulated Annealing
Hill Climber
(...)

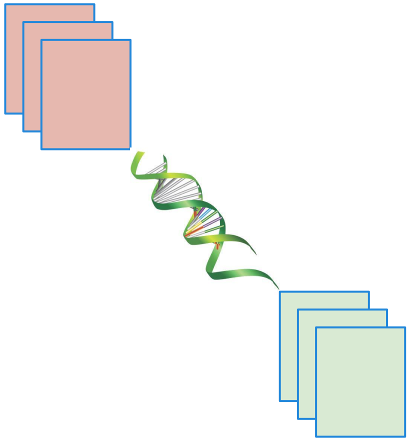
The Fitness Functions (Feedback Strategies)

Distance to Coverage Goals
Count of Executions Thrown
Input or Output Diversity
(...)

(Goals)

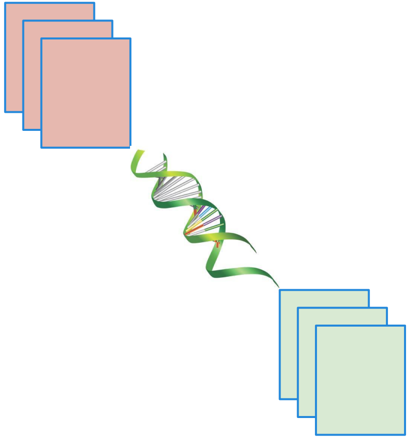
Cause Crashes
Cover Code Structure,
Generate Covering Array,
(...)

The Metaheuristic



- Decides how to select and revise solutions.
  - Changes approach based on past guesses.
  - Fitness functions give feedback.
  - Population mechanisms choose new solutions and determine how solutions evolve.

The Metaheuristic



- Decides how to select and revise solutions.
  - Small adjustments **(local search)** or sampling from the whole space **(global search)**.
  - One solution at a time or entire populations.
  - Often based on natural phenomena (swarm behavior, evolution).
  - Trade-off between speed, complexity, and understandability.

“Solutions”

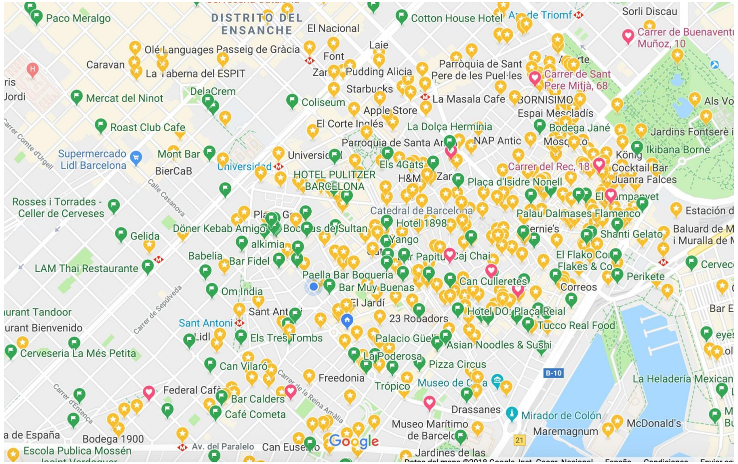
- What is a solution?
  - **Test Case:** Evolved in isolation from other test cases.
  - **Test Suite:** A set of test cases, evolved together.
- Depends on how goal attainment measured.
  - Code Coverage
    - Test Case: Target one code section at a time.
    - Test Suite: Target coverage of entire class/system.

Local Search

- Generate and score a potential solution.
- Attempt to improve by looking at its **neighborhood**.
  - Make small, incremental improvements.
- Very fast, efficient if good initial guess.
  - Get “stuck” if bad guess.
  - Often include reset strategies.

Exploring the Neighborhood

- Small changes to solution.
  - For each call:
    - Switch value of boolean, other values from an enumerated set, bounded range of numeric choices.
  - Full test case:
    - Insert a new call.
    - Delete or replace an existing call.
      - Can replace by changing the function called or its parameters.

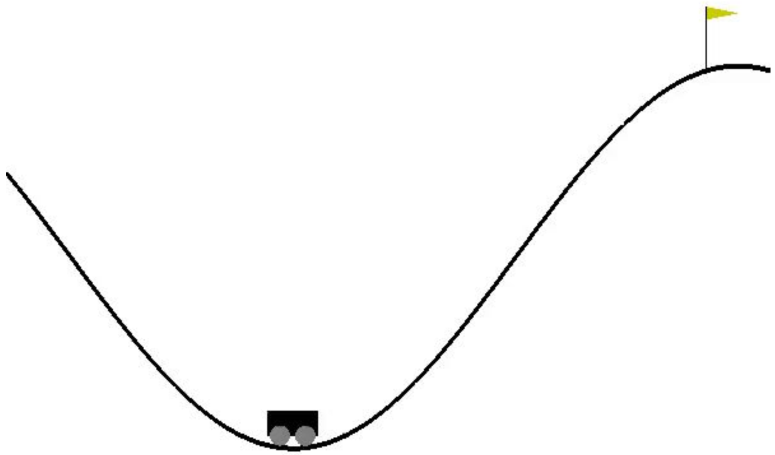


Hill Climbing

- Pick a initial solution at random.
- Examine the local neighborhood.
- Choose the best neighbor and “move” to it.
- Repeat until no better solution can be found.
  - Climbs mountains in fitness function landscape.
  - Restart when no improvement can be found.

Hill Climbing Strategies

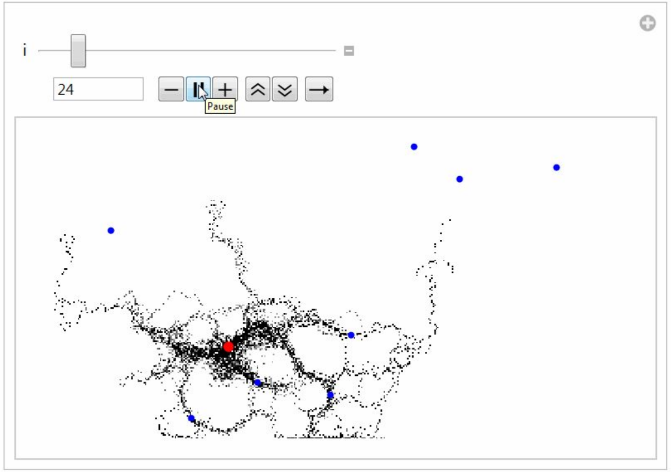
- **Steepest Ascent**
  - Examine all neighbors
  - Pick one with highest improvement.
- **Random Ascent**
  - Examine random neighbors.
  - Choose first to show *any* improvement.



Simulated Annealing

- Choose a neighboring test case.
    - If better, select it. If not, select it at probability:
      prob(score, newScore, time, temp) = $e^{((score - newScore) * (time / temp))}$
    - Governed by temperature function:
      temp(time, maxTime) = (maxTime - time) / maxTime
- Initially, large jumps around search space.
    - Stabilizes over time.

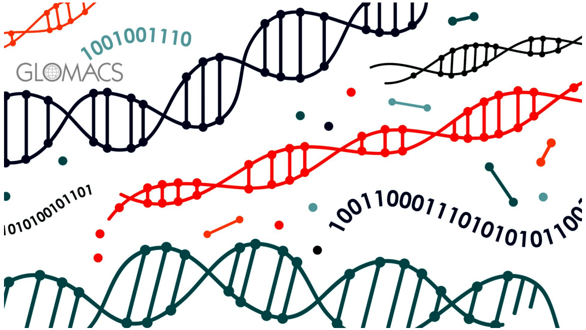
Global Search



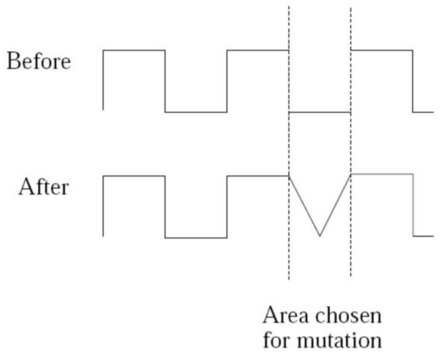
- Generate multiple solutions.
- Evolve by examining whole search space.
- Typically based on natural processes.
  - Swarm patterns, foraging behavior, evolution.
  - Models of how populations interact and change.

Genetic Algorithms

- Over multiple generations, evolve a population.
  - Good solutions persist and reproduce.
  - Bad solutions are filtered out.
- Diversity is introduced by:
  - Keeping the best solutions.
  - Some random solutions.
  - Creating “offspring” through **mutation** and **crossover**.

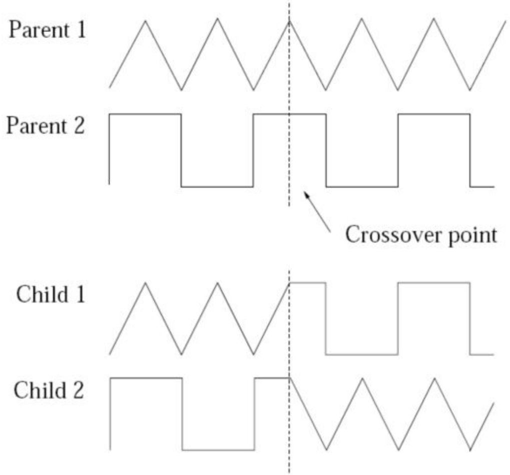


Genetic Algorithms - Mutation



- Copy a high-scoring solution.
- Impose a small change.
  - (add/delete/modify a function call, change an input value)
  - Follow the rules for determining the neighbors of a test.
  - Choose a neighbor from that set.

Genetic Algorithms - Crossover



- By “breeding” two good tests, we may produce better tests.
- Form two new solutions.
  - Sample from probability distribution to decide which parent to inherit from.

Genetic Algorithms - Crossover

- One Point Crossover
  - Splice at crossover point.

A	B	C	D	A	B	3	4
1	2	3	4	1	2	C	D

- Uniform Crossover
  - Flip coin at each line, second child gets other option.

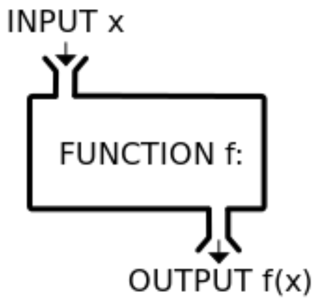
A	B	C	D	A	2	3	D
1	2	3	4	1	B	C	4

- Discrete Recombination
  - Flip coin at each line for both children.

A	B	C	D	A	2	C	4
1	2	3	4	A	B	3	4

Let’s take a break.

Fitness Functions



- Domain-based scoring functions that determine how good a potential solution is.
  - Should offer feedback:
    - Percentage of goal attained.
    - *Better - information on how to improve solution.*
  - **Can optimize more than one at once.**
    - Independently optimize functions
    - Combine into single score.

Example - Code Coverage

- **Goal:** Attain Branch Coverage over the code.
  - Tests reach branching point (i.e., if-statement) and execute all possible outcomes.
- **Fitness function (Attempt 1):**
  - Measure coverage and try to maximize % covered.
  - **Good:** Measurable indicator of progress.
  - **Bad:** No information on how to improve coverage.

Example - Code Coverage

- Attempt 2: Distance-Based Function
- **fitness = branch distance + approach level**
  - **Approach level**
    - Number of branching points we need to execute to get to the target branching point.
  - **Branch distance**
    - If other outcome is taken, how “close” was the target outcome?
    - How much do we need to change program values to get the outcome we wanted?

Example - Code Coverage

```
if(x < 10){ // Branch 1
    // Do something.
}else if (x == 10){ // Branch 2
    // Do something else.
}
```

Goal: Branch 2, True Outcome

Approach Level

- If Branch 1 is true, approach level = 1
- If Branch 1 is false, approach level = 0

Branch Distance

- If x==10 evaluates to false, branch distance = (abs(x-10)+k).
- Closer x is to 10, closer the branch distance.

Other Common Fitness Functions

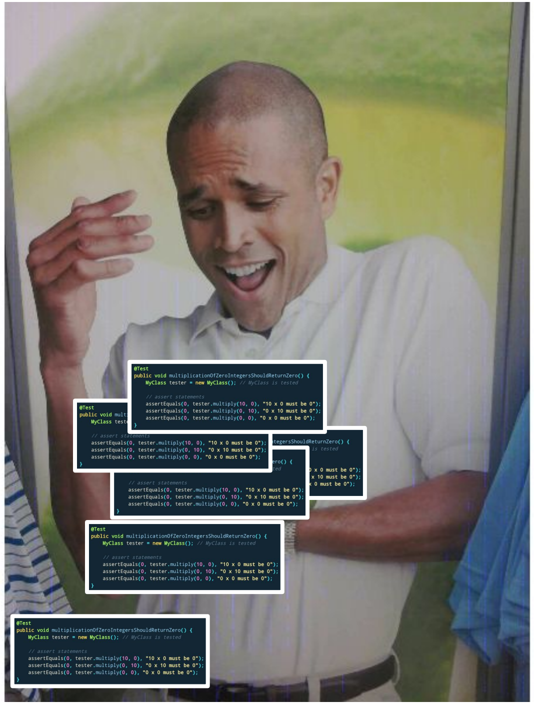
- Number of methods called by test suite
- Number of crashes or exceptions thrown
- Diversity of input or output
- Detection of planted faults
- Amount of energy consumed
- Amount of data downloaded/uploaded
- **… (anything that reflects what a *good* test is)**

What are your testing goals?

(and would they make good fitness functions?)

What Do I Do With These Inputs?

- If looking for crashes, just run generated input.
- If you need to judge correctness, add assertions.
  - General properties, not specific output.
    - **No**: `assertEquals(output, 2)`
    - **Yes:** `assertTrue(output % 2 == 0)`



Generating Covering Arrays for Combinatorial Interaction Testing

CIT

Allow Content to Load	Notify About Pop-Ups	Allow Cookies	Warn About Add-Ons	Warn About Attack Sites	Warn About Forgeries
Allow	Yes	Allow	Yes	Yes	Yes
Restrict	No	Restrict	No	No	No
Block		Block			

- Instead of testing all combinations, test all 2-way interactions.
- **Covering Array:** A set of test specifications that covers all pairs of values.
  - From 144 specifications to 9
- Generating **smallest** covering array NP-hard.
- Metaheuristic search can easily generate near-smallest covering array.

Allow Content	Allow Cookies	Pop-Ups	Add-Ons	Attacks	Forgeries
Allow	Allow	Yes	Yes	Yes	Yes
Allow	Restrict	No	No	-	No
Allow	Block	No	No	No	Yes
Restrict	Allow	Yes	No	No	No
Restrict	Restrict	Yes	-	-	Yes
Restrict	Block	No	Yes	Yes	No
Block	Allow	No	-	-	Yes
Block	Restrict	-	Yes	No	-
Block	Block	Yes	No	Yes	No

Generating Covering Arrays

1. Generating Random Solutions
2. Calculating Solution Fitness
3. Evolving Solutions
   a. Mutation (Genetic Algorithm) / Neighboring Solution (Local Search)
   b. Crossover (Genetic Algorithm)

Generating Random Solution

1. Calculate list of pairs to cover.
2. Until list is empty:
   a. Generate random test specification.
   b. Remove covered pairs from list.
   c. Add specification to covering array.
3. Return covering array.

(Content = Allow, Pop-Ups = Yes)
(Content = Allow, Pop-Ups = No)
(Content = Restrict, Pop-Ups = Yes)
…

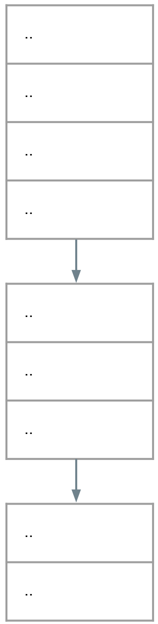
Allow	No	Block	No	Yes	Yes

(Content = Allow, Pop-Ups = Yes)
~~(Content = Allow, Pop-Ups = No)~~
(Content = Restrict, Pop-Ups = Yes)
…

..	..	..	..	..	..
Allow	No	Block	No	Yes	Yes

Fitness Function

- Size of the covering array.
  - `coveringArray.length();`
  - Want to minimize the score (smaller arrays are better)
- Can be measured, fast calculation.
- Tells us which solutions are better.
- Does not offer detailed feedback, but still works.

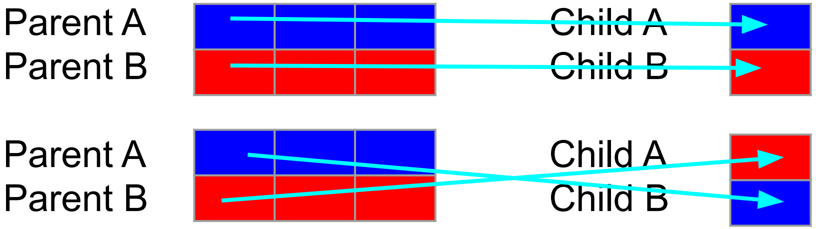


Mutation

- Change a value in a test specification.
  - Set a limit on number of changes made at one time.
  - Maybe we can make it smaller with a few changes?
- If all pairs covered in fewer tests, discard remainder.
- If no longer a covering array:
  - Throw out solution OR
  - Revert change and try again OR
  - Revert change and mutate different solution.

Crossover

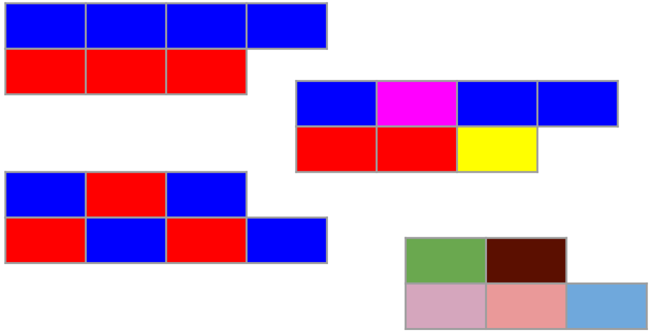
- Take two covering arrays, create two “child” arrays.
- For each specification, flip a coin:
  - Heads:
  - Tails:



- Check each child:
  - If not a covering array, discard.
  - If still a covering array, remove redundant specifications.

Search Process

- Generate population at random.
- Score each by size.
- Create new population.
  - Retain best arrays (10%)
  - Create mutations (30%)
  - Create children (30%)
  - Generate random (30%)
- Repeat until budget expires.



Not Just Test Generation...

Can be applied to any problem with:

- Large search space.
- Fitness function and solution generation with low computational complexity.
- Approximate continuity in fitness function scoring.
- No known optimal solution.

Automated Program Repair

- Produce patches for common bug types.
- Many bugs can be fixed with just a few changes to the source code - inserting new code, and deleting or moving existing code.
  - Add null values check.
  - Change conditional expression.
  - Move a line within a try-catch block.

Generate and Validate

- **Genetic programming** - solutions represent sequences of edits to the source code.
- **Generate and validate approach**:
  - Fitness function: how many tests pass?
  - Patches that pass more tests create new population:
    - Mutation: Change one edit into another.
    - Crossover: Merge edits from two parent patches.

GenProg Results

- Repaired 55/105 bugs at average $8 per bug.
  - Projects with over 5 million lines of code
  - Supported by 10000 test cases.
- Patch infinite loops, segmentation faults, buffer overflows, denial of service vulnerabilities, “wrong output” faults, and more.

Risks of Automation

- Structural coverage is important.
  - Unless we execute a statement, we're unlikely to detect a fault in that statement.
- More important: how we execute the code.
  - Humans incorporate context from a project.
  - "Context" is difficult for automation to derive.
  - One-size-fits-all approaches.

Limitations of Automation

- Automation produces different tests than humans.
    - “shortest-path” approach to attaining coverage.
    - Apply input different from what humans would try.
    - Execute sequences of calls that a human might not try.
- Automation **can be** very effective, but more work is needed to improve it.

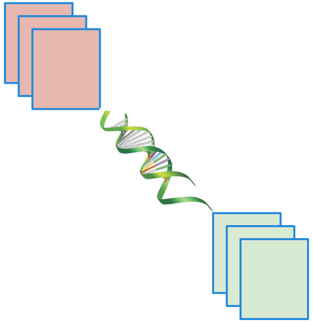
I Want to Try This Out!

- Fuzzing often based on metaheuristic search.
  - AFL (American Fuzzy Lop), Google OSS-Fuzz use genetic algorithms, fitness = code coverage.
    - http://lcamtuf.coredump.cx/afl/
    - https://google.github.io/oss-fuz
    - system-level tests
  - The Fuzzing Book has tutorials and code for many specialized approaches:
    - https://www.fuzzingbook.org/

I Want to Try This Out!

- EvoSuite generates JUnit tests for Java
  - http://www.evosuite.org/
- Sapienz (Facebook) tests Android/iOS apps
  - Will be open-source by ~~end of 2020~~ 2021?.
  - Older version available
    - https://github.com/Rhapsod/sapienz/
- Have a specialized goal?
  - NSGA-II: customizable open-source genetic algorithm: https://www.iitk.ac.in/kangal/codes.shtml

Summary



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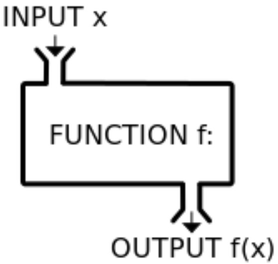

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The Metaheuristic (Algorithm)

Genetic Algorithm
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The Fitness Functions (Feedback Strategies)

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Count of Executions Thrown
Input or Output Diversity
(...)

(Goals)

Cause Crashes
Cover Code Structure,
Maximize Battery Use,
(...)

Next Time

- Review and Course Summary
  - Individual assignment details on Canvas

- Assignment 4 - Due Sunday
- Assignment 5 posted.
  - Questions?

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