CHALMERS UNIVERSITY OF TECHNOLOGY | UNIVERSITY OF GOTHENBURG

Lecture 12: Automated Test Case Generation

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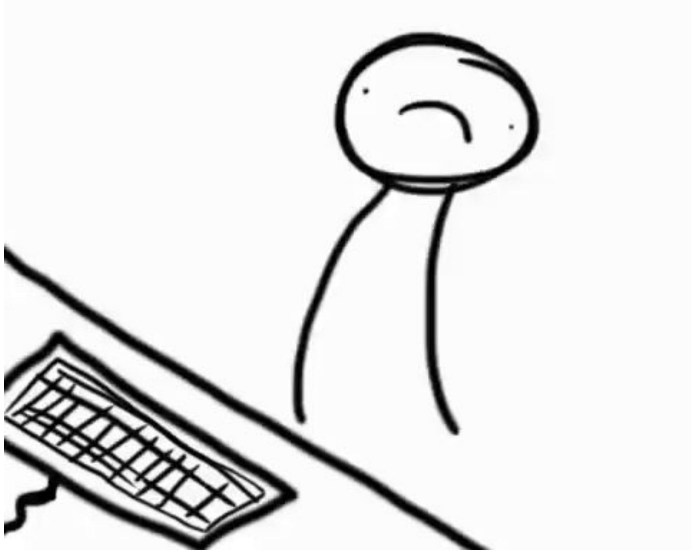
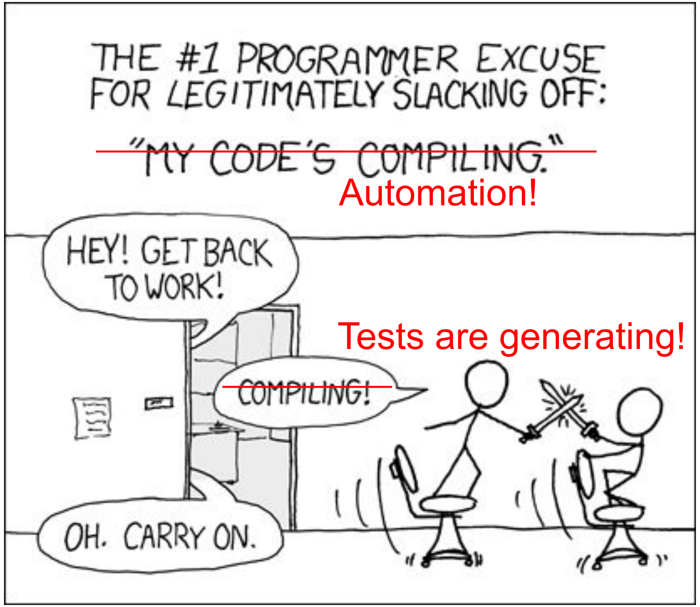
Automating Test Creation

- 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 check for crashes, memory leaks, other problems that can be measured automatically.

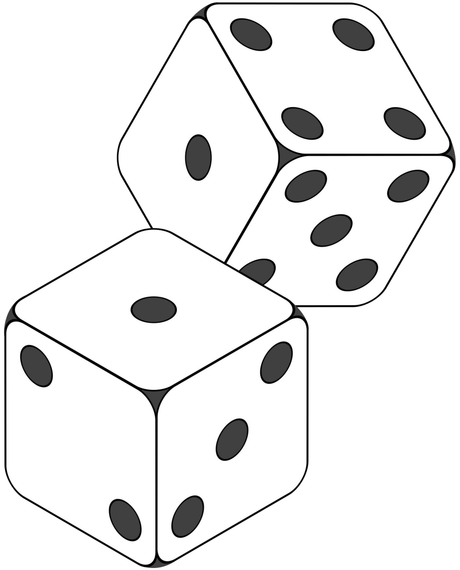


Today's Goals

- Introduce Search-Based Test Generation
  - (AKA: Fuzzing)
  - Test Creation as a Search Problem
    - Metaheuristic Search Algorithms
    - Fitness Functions

Random Generation

- Randomly formulate test cases.
  - 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 you run out of time.



Example - BMI Calculation

$$BMI = \frac{weight}{(height)^2}$$

	Age						
Classification	$[2,4]$	$(4,7]$	$(7,10]$	$(10,13]$	$(13,16]$	$(16,19]$	> 19
Underweight	≤ 14	≤ 13.5	≤ 14	≤ 15	≤ 16.5	≤ 17.5	< 18.5
Normal weight	≤ 17.5	≤ 14	≤ 20	≤ 22	≤ 24.5	≤ 26.5	< 25
Overweight	≤ 18.5	≤ 20	≤ 22	≤ 26.5	≤ 29	≤ 31	< 30
Obese	> 18.5	> 20	> 22	> 26.5	> 29	> 31	< 40
Severely obese	—	—	—	—	—	—	≥ 40

BMICalc
height weight age
bmi_value() classify_bmi_adults() classify_bmi_teens_and_children()

Example - BMI Calculation

```
def test_bmi_value_valid():
    bmi_calc = BMICalc(150, 41, 18)
    bmi_value = bmi_calc.bmi_value()
    assert  bmi_value == 18.2

def test_bmi_adult():
    bmi_calc = BMICalc(160, 65, 21)
    bmi_class = bmi_calc.classify_bmi_adults()
    assert bmi_class == "Overweight"

def test_bmi_children_4y():
    bmi_calc = BMICalc(100, 13, 4)
    bmi_class = bmi_calc.classify_bmi_teens_and_children()
    assert bmi_class == "Underweight"
```

BMICalc
height weight age
bmi_value() classify_bmi_adults() classify_bmi_teens_and_children()

Random Generation - BMI Example

- Create an empty test case:

```
def test_1():
```

- Instantiate the class-under-test with random values:

```
def test_1():
    cut = BMICalc(180, 50, 40)
```

- Insert 1+ method calls or assignments to class variables.
  - Number of calls is random
  - Which method/variable is random
  - Method parameters are random values

BMICalc
height weight age
bmi_value() classify_bmi_adults() classify_bmi_teens_and_children()

```
def test_1():
  cut = BMICalc(180, 50, 40)
  output = cut.bmi_value()
  cut.height = 15681
  output2 = cut.classify_bmi_adults()
```

Random Search

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

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.
- Search-based test generation based on **guess-and-check** process.

Test Creation as a Search Problem

- Many testing goals can be measured:
  - How many exceptions were thrown?
  - How many representative output values were returned?
  - What percentage of lines of code were covered?
  - How diverse is our input?
- If goal can be measured, search can be automated.

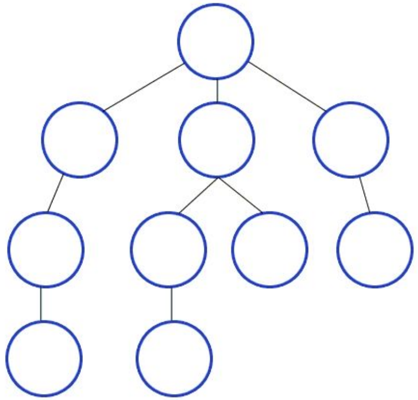
Search-Based Test Generation

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

Search Strategy

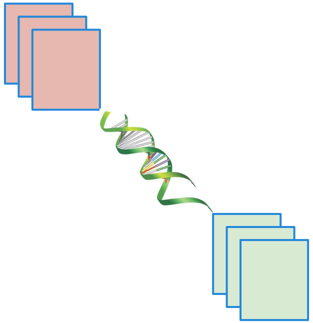
- The order that solutions are tried is the key to efficiently finding a solution.
- A search follows some defined strategy.
  - Called a "**metaheuristic**".
- Metaheuristics are used to choose solutions and to ignore solutions known to be unviable.
  - Smarter than pure random guessing!

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.

Search-Based Test Generation



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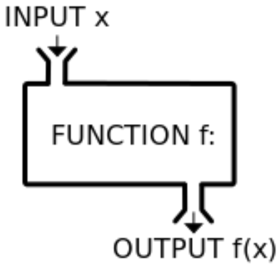

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The Metaheuristic (Sampling Strategy)

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,
(...)

Solution Representation

Solution Representation

- Must decide what a solution “looks like”.
- For unit testing:
  - A solution is a test suite.
  - A test suite contains 1+ test cases.
  - Each test case interacts with a class-under-test.
  - Each test case initialized the class-under-test.
  - Each test case contains one or more actions.
    - An action is a method call or variable assignment.
    - Each action has parameters (method parameters or values to assign to variables).

External vs Internal Representation

Internal (Genotype) Representation Can be easily manipulated by metaheuristic	**External (Phenotype) Representation** Executable, human-readable

Test Suite

Test Case

```
[
    [
        [-1, [246, 680, 2]],
        [2, [18]],
        [4, []],
        [1, [466]],
        [5, []],
        [4, []],
        [1, [26]],
        [5, []]
    ]
]
```

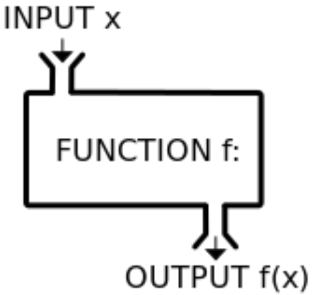
Actions, with ID (method or variable), parameters

```python
import pytest
import bmi_calculator

def test_0():
    cut = bmi_calculator.BMICalc(246,680,2)
    cut.age = 18
    cut.classify_bmi_teens_and_children()
    cut.weight = 466
    cut.classify_bmi_adults()
    cut.classify_bmi_teens_and_children()
    cut.weight = 26
    cut.classify_bmi_adults()
```

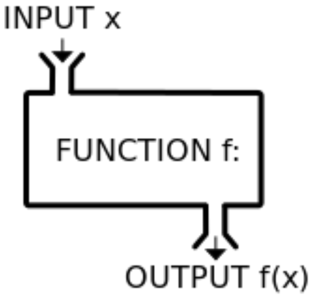
Fitness Functions

Fitness Functions



- Domain-based scoring functions that determine how good a potential solution is.
  - Should represent goals of tester.
  - Must return a numeric score.
    - % of a checklist
    - raw number
    - NOT Boolean (no feedback)
  - Can be maximized or minimized.

Fitness Functions



- Should offer feedback:
  - Small change in solution should not lead to large change in score.
  - Informative functions calculate *distance* to optimality.
- **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 must reach all branching points (i.e., if-statement) and execute all possible outcomes.

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

In this code:

- Two Branches
- Each must evaluate to `true` and `false`.

Example - Code Coverage

- **Goal:** Attain Branch Coverage over the code.
- **Fitness function (Basic):**
  - Measure coverage and try to maximize % covered.
  - **Good:** Measurable indicator of progress. Can use standard tools (pytest-cov, Cobertura).
  - **Bad:** No information on how to improve coverage.

Example - Code Coverage

- Advanced: 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 - Branch 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)**

Bloat Penalty

- Small penalty subtracted from fitness.
- Limits number of tests and number of actions.

$$bloat\_penalty(solution) = (num\_test\_cases/num\_tests\_penalty) + (average\_test\_length/length\_test\_penalty)$$

ex. 10

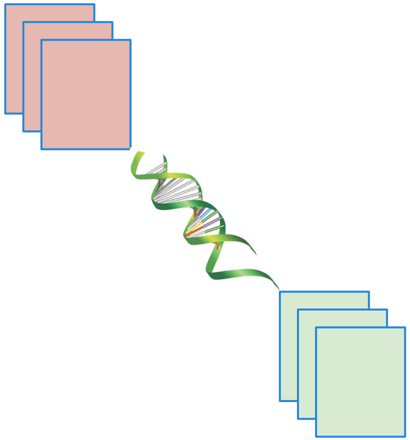
ex. 30

- Important not to penalize too heavily.

Let’s take a break.

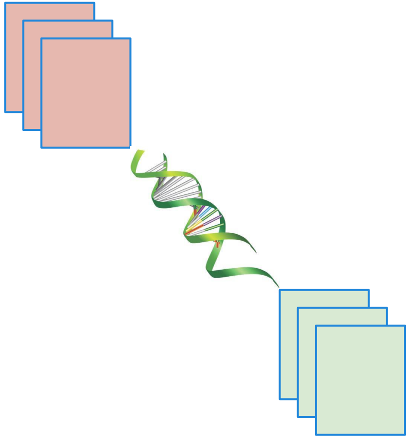
Metaheuristic Algorithms

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 changes to single solution **(local search)** or larger changes to multiple solutions **(global search)**.
  - Often based on natural phenomena (swarm behavior, evolution).
  - Trade-off between speed, complexity, and understandability.

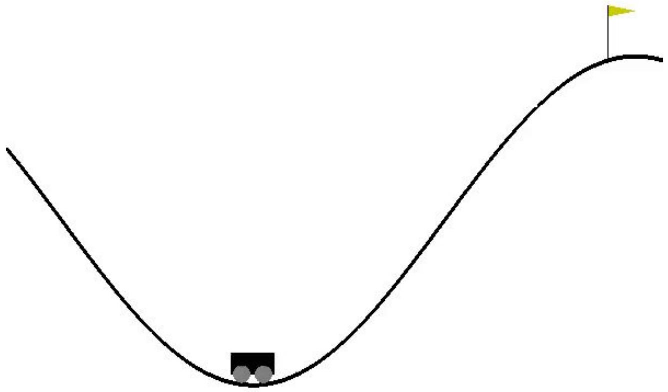
How Long Do We Spend Searching?

- 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.*

Local Search

- Generate and score a single 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.

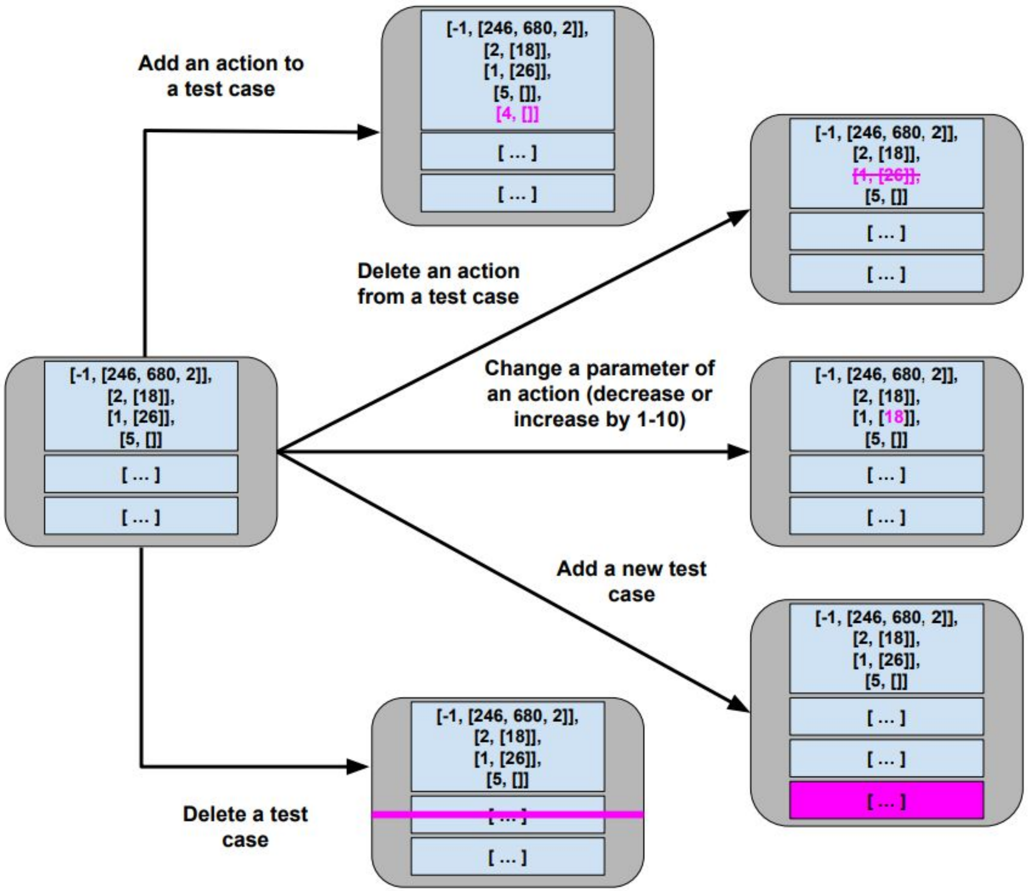
Hill Climbing



- Generate a random initial solution.
- Each generation (while budget remains):
  - Attempt up to `max_tries` *mutations* to the solution.
    - If a mutation results in a better solution, set this as the new solution.
    - Keep track of the best mutation seen to date.
  - If we run out of tries, reset to a new random initial solution.

Mutation

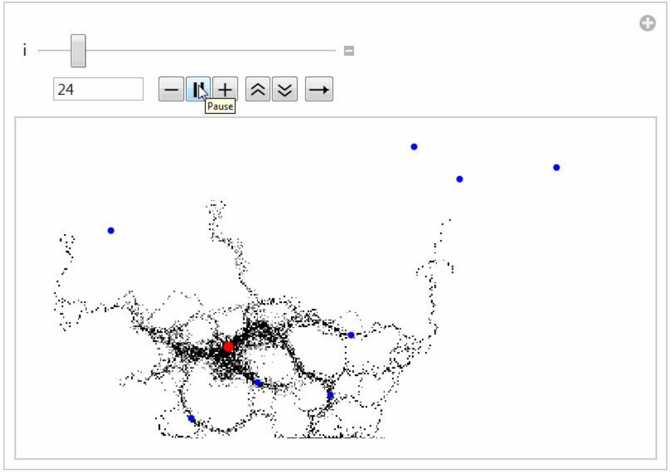
- Small change to current solution.
- Impose one of these changes at a time:



Hill Climber

- User-Controlled Parameters:
  - Maximum mutations before a restart (ex: 200)
  - Maximum number of restarts (ex: 5)
- Easy to implement, faster than many other metaheuristics.
  - Reliant on initial guesses and restarts.

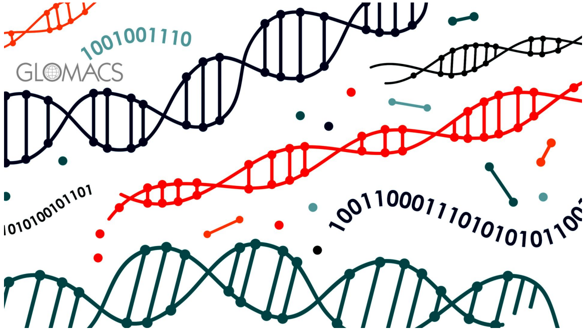
Global Search



- 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 Algorithm

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

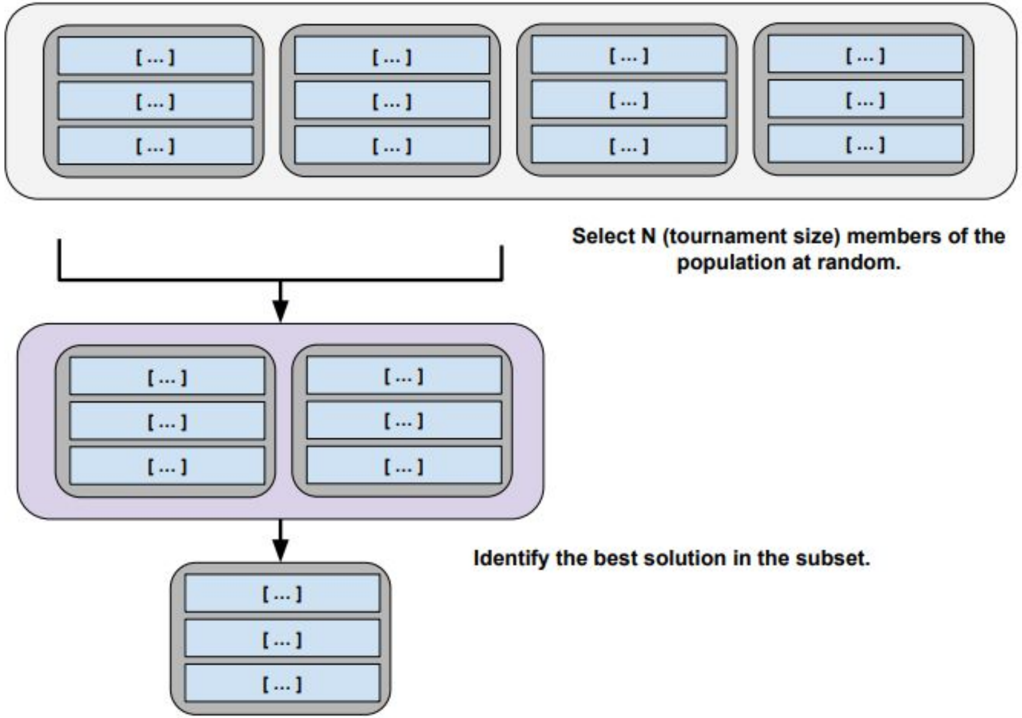


Genetic Algorithm

- Create a random initial population.
- Start a new generation (while budget remains):
  - Create new empty population.
  - While space remains:
    - **Select** two “good” members of current population.
    - At a small probability, replace these members with “children” combining genes of members (**crossover**).
    - At a small probability, **mutate** each member.
    - Add members to new population.
  - If no better solution is found for N generations, terminate early (**stagnation**).

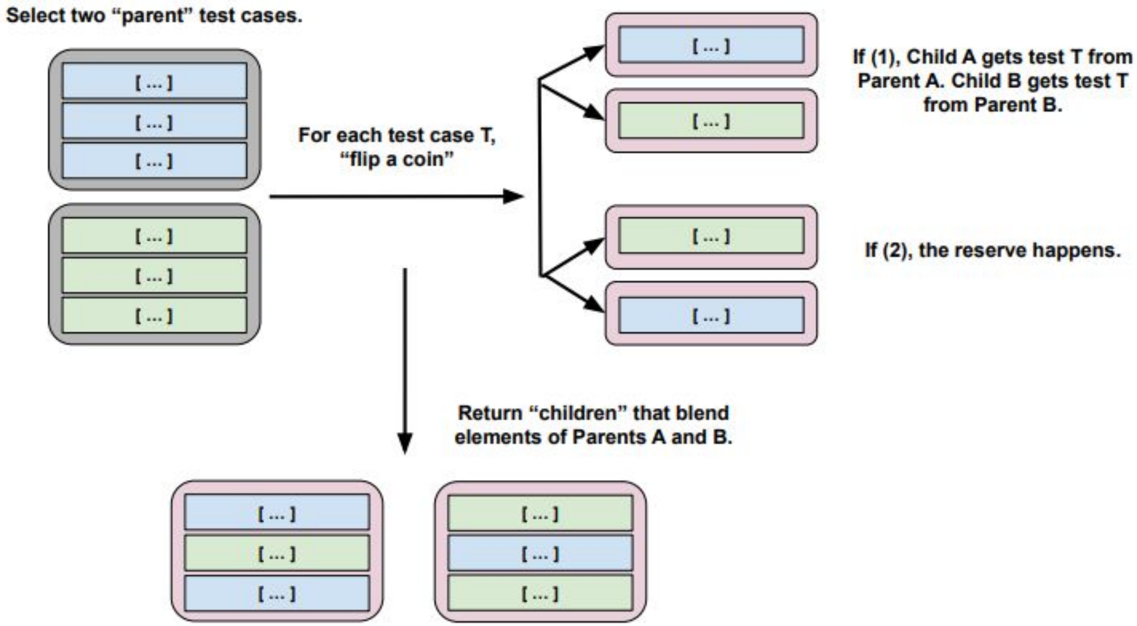
Selection

- Rather than searching for best population member:
  - Select a random subset.
  - Calculate fitness for each.
  - Return best.



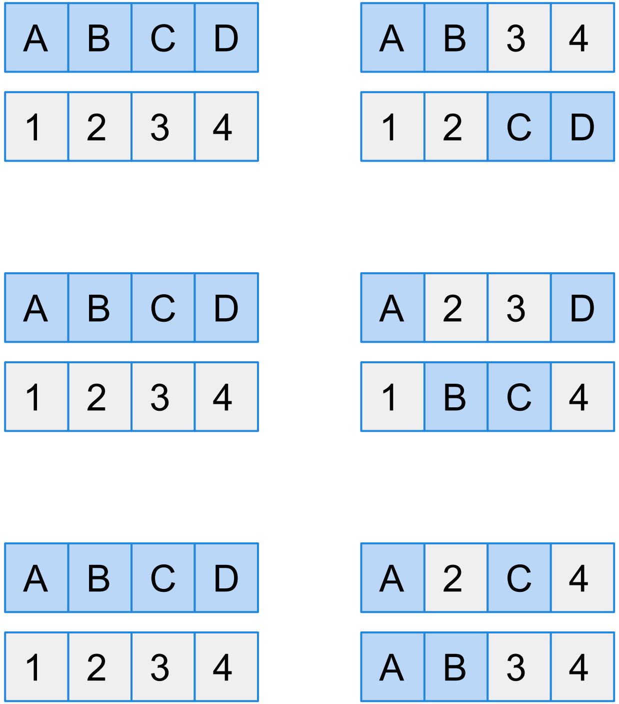
Crossover

- Creates two “child” solutions by combining tests from each parent solution.



Crossover

- Single-Point Crossover
  - Splice at crossover point.
- Uniform Crossover
  - Flip coin at each test, second child gets other option.
- Discrete Recombination
  - Flip coin at each test for both children.



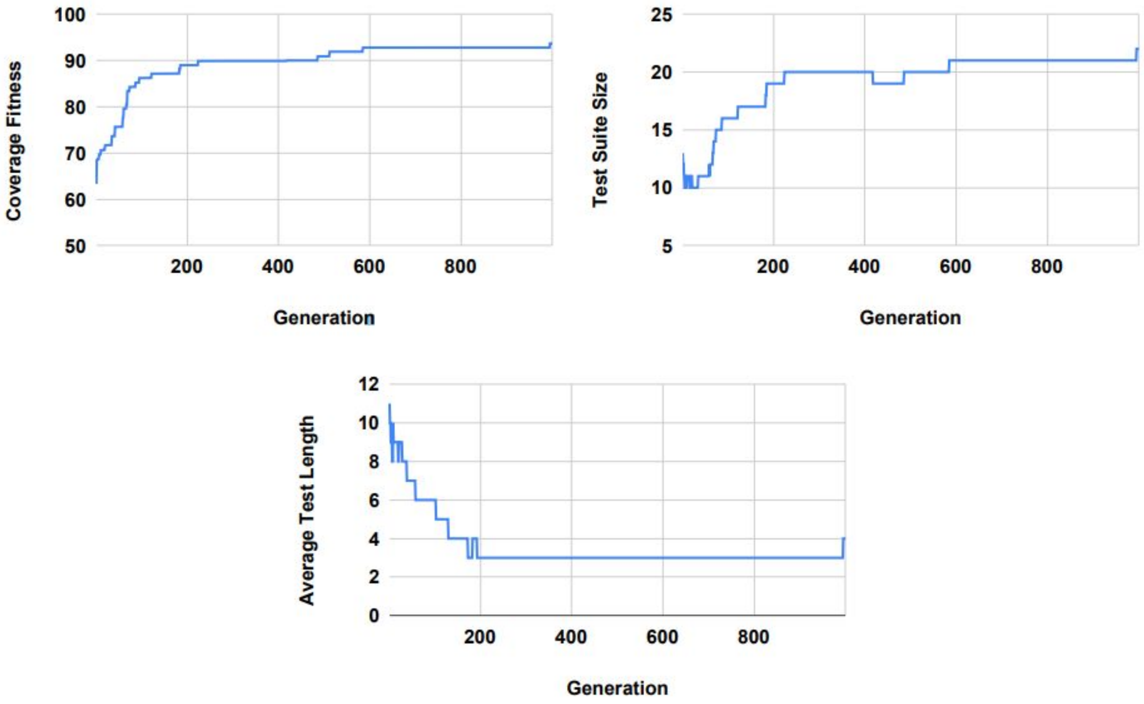
Genetic Algorithm Parameters

- All parameters affect solution quality. Usually some experimentation required.
  - **Population Size** (default: 20)
  - **Tournament Size** (# population members compared during selection, default: 6)
  - **Crossover Probability** (default: 0.7)
  - **Mutation Probability** (default: 0.7)
  - **Stagnation Threshold** (# generations without improvement before ending, default: 30)

Examining the Resulting Test Suites

1000 Generations of Evolution

- Genetic Algorithm run for 1000 generations for BMICalc.
- Stagnation turned off.
- Highly variable until ~ 200 generations, then small changes afterwards.



Examples of Generated Test Cases

```
def test_0():
    cut = bmi_calculator.BMICalc(120,860,13)
        cut.classify_bmi_teens_and_children()

def test_2():
        cut = bmi_calculator.BMICalc(43,243,59)
        cut.classify_bmi_adults()
        cut.height = 526
        cut.classify_bmi_adults()
        cut.classify_bmi_adults()

def test_5():
        cut = bmi_calculator.BMICalc(374,343,17)
        cut.age = 123
        cut.classify_bmi_adults()
        cut.age = 18
        cut.classify_bmi_teens_and_children()
        cut.weight = 396
        cut.classify_bmi_teens_and_children()
```

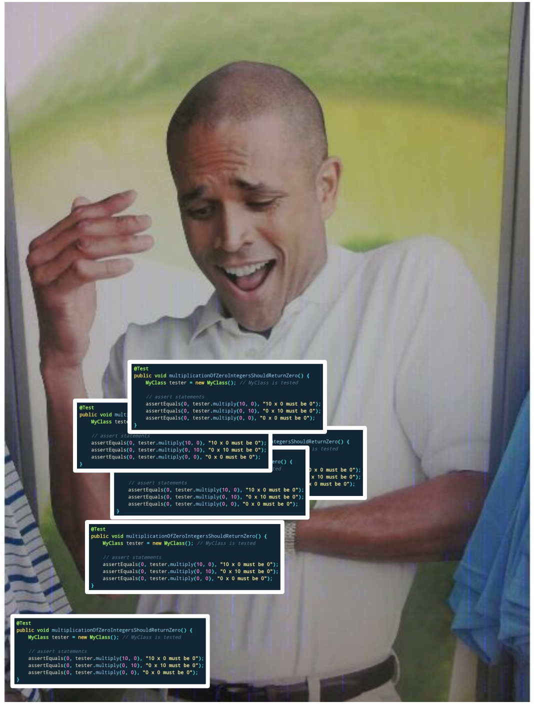
```
def test_7():
        cut = bmi_calculator.BMICalc(609,-1,94)

def test_11():
        cut = bmi_calculator.BMICalc(491,712,20)
        cut.classify_bmi_adults()

def test_17():
        cut = bmi_calculator.BMICalc(608,717,6)
        cut.classify_bmi_teens_and_children()
        cut.age = 91
        cut.classify_bmi_teens_and_children()
        cut.classify_bmi_teens_and_children()
```

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)`



Additional Concepts

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.

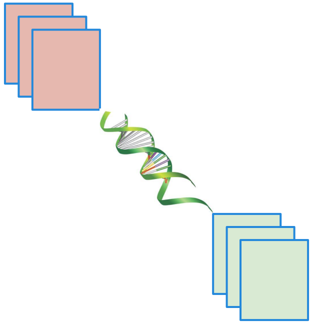
I Want to Try This Out!

- 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!

- Python:
  - Tutorial for beginners: https://greg4cr.github.io/pdf/21ai4se.pdf
  - https://github.com/Greg4cr/PythonUnitTestGeneration
- EvoSuite for Java: http://www.evosuite.org/
- Sapienz (Facebook) tests Android/iOS apps
  - Will be open-source in ~~end of 2020~~ 2022?.
  - Older version available
    - https://github.com/Rhapsod/sapienz/

Summary



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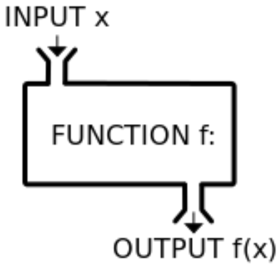

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Distance to Coverage Goals
Count of Executions Thrown
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(...)

(Goals)

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

Next Time

- **Exercise Session - Mutation Testing**
- Model-Based Testing and Verification
  - Reading: Pezze and Young, Ch 5.5, 8, 14
- Assignment 2 - Due February 26
  - Questions?
- Assignment 3 - Due March 12
  - Based on Fault-Based Testing (Lec 11) and Model-Based Testing/Verification (Lectures 13-14)

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