FACULDADE ENGENHARIA
Departamento de Informática

Qualidade de Software
(14450)

Automated Test Case Generation

(adapted from lecture notes of the “DIT 635 - Software Quality and Testing” unit,
delivered by Professor Gregory Gay, at the Chalmers and the University of Gothenburg, 2022 and “Using Genetic Algorithms to Automatically Generate Unit Tests - Software Quality” dissertation by Manuel Magalhães, at Universidade da Beira Interior, 2024)

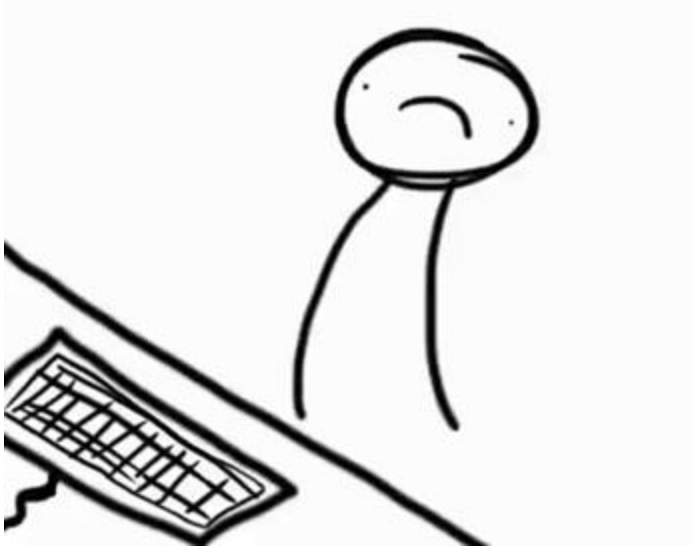
Today's Goals

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

Automating Test Creation

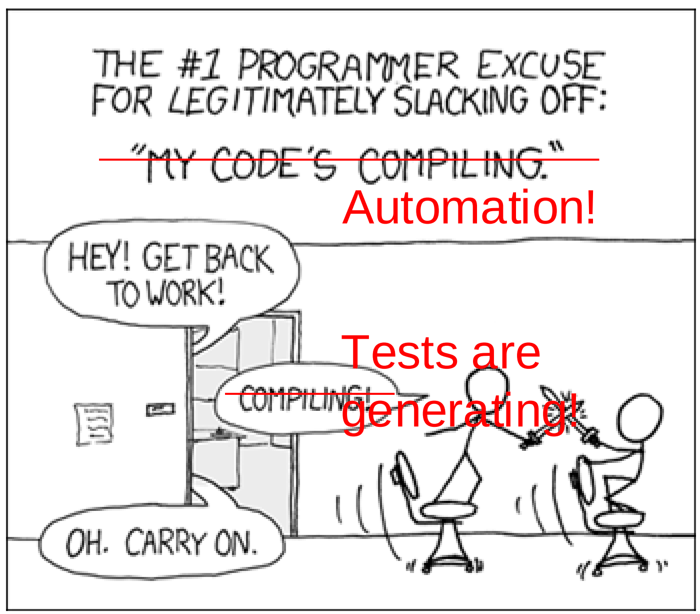
✧ Testing is invaluable, but expensive.

- 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.



Test Automation

- **Test Automation** is the development of software to separate repetitive tasks from the creative aspects of testing.
- Automation allows control over *how* and *when* tests are executed.
  - Control the environment and preconditions.
  - Automatic comparison of predicted and actual output.
  - Automatic hands-free re-execution of tests.

Manual vs Automation

- Scaling
  - Manual generation can be an exhaustive and a time-consuming process. It scales with the size of the project, which can hinder the development speed of the software;
  - Automated generation, being an automated process, can help reduce the time needed to perform testing activities;

- Coverage and Mutation
  - Automated generation of unit tests usually provides a higher capability of achieving better coverage values than the manual approach;
  - The ability to identify mutants in unit tests (identification of allocated defects) is generally better in unit tests generated automatically;

Manual vs Automation

- Fault Detection
  - Automated generation identifies more instances of real faults than the manual generation;
  - Allocated defects by mutation testing is not the same as defects introduced during the project development, such as regression faults.

- Cost efficiency
  - Automated generation, despite also using human resources, requires an additional cost which is machine resources;
  - The automated generation approach presents very low costs and overall better cost efficiency in terms of testing time.

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

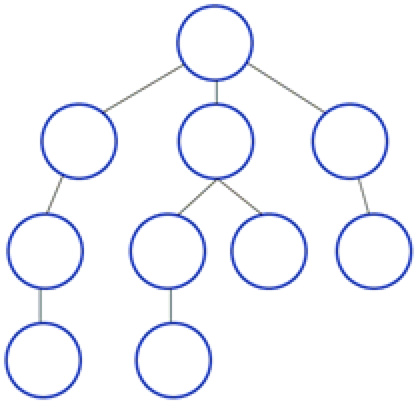
- **Make one or more guesses.**
  - Generate one or more individual test cases or full suites.
- **Check suitableness to a specific goal.**
  - Score each test case or full suites.
- **Search around a space of solutions**
  - Select a set of possible solutions according to a predefined goal.
- **Try until time runs out or termination criteria is reached.**
  - 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.



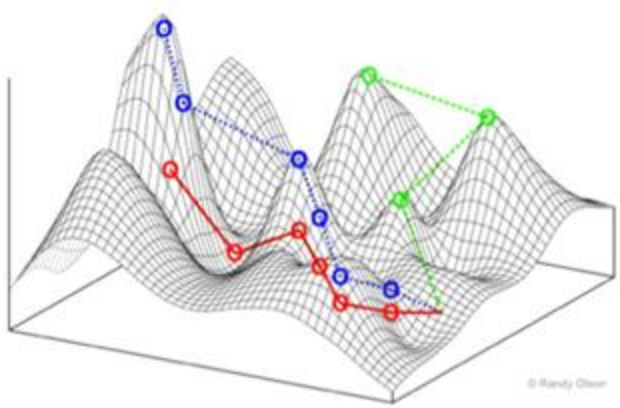
- ✧ Attempt to estimate shortest path.
  - A* search examines distance traveled and estimates optimal next step.
  - Requires domain-specific scoring function.

How Long Do We Spend Searching?

- ✧ Exhaustive search not viable due to computational and temporal constraints.
- ✧ Search can be bound by a **search budget**.
  - Limit for solution's evaluations
  - Time allotted to the search (number of minutes/seconds);
  - Search iteration limit
- ✧ **Optimization problem**:
  - Improve the solutions during the search;
  - Find the best solution possible in the search space before time runs out or search budget is reached.

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 makes a solution good.
  - In practice, **efficiency in both categories is desired**.

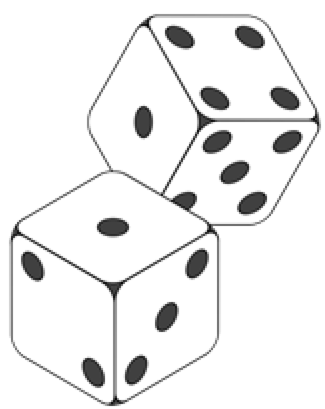


Random Search

✧ Randomly formulate a solution.

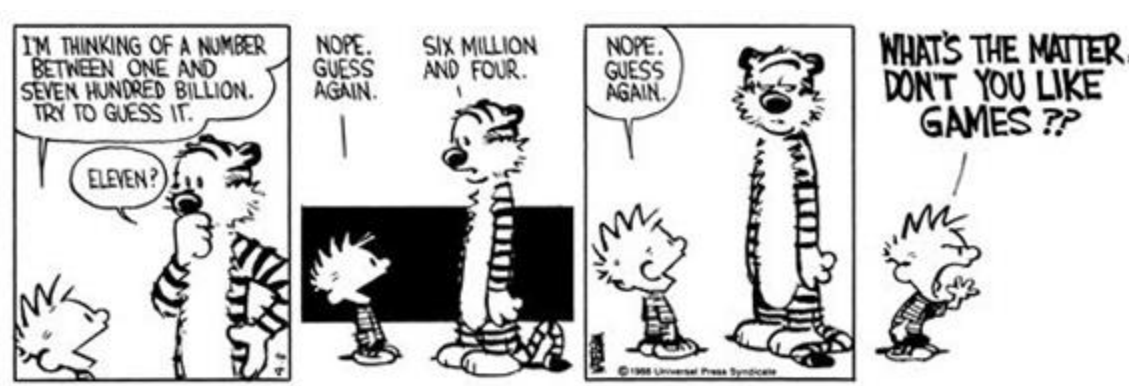
- Unit testing: choose a class in the system, choose random methods, call with random parameter values.
- System-level testing: choose an interface, choose random functions from interface, call with random values.

✧ Keep trying until goal attained or budget expires.



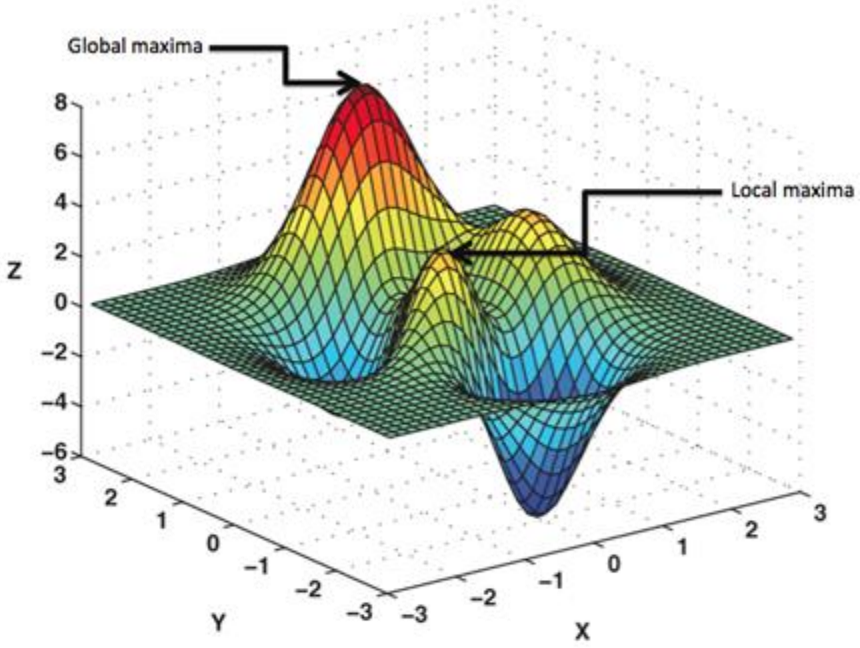
Random Search

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



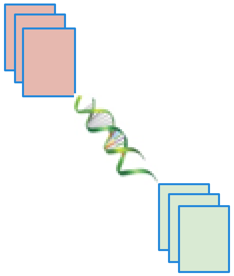
Metaheuristic Search

- 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.

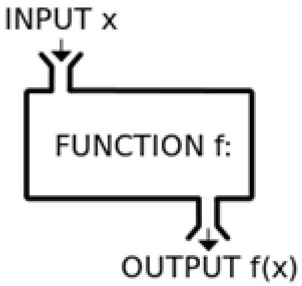


Mechanics of Optimization

AKA: How can I get a computer to search?

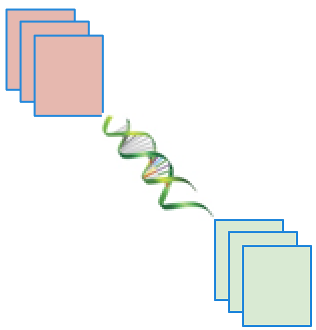


Metaheuristic



Fitness Function(s)

Search-Based Test Generation



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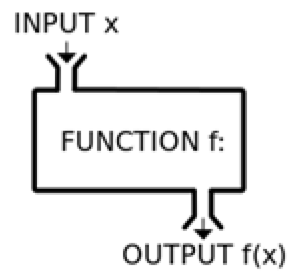

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The Metaheuristic (Sampling Strategy)

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 to guide the metaheuristic for better solutions.
  - Population mechanisms choose new solutions and determine how solutions evolve.
  - Formulation of new sampling strategies during the search.

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 (chromosomes evolution).
  - Trade-off between speed, complexity, and understandability.
- Metaheuristic algorithms
  - Hill Climber;
  - Genetic Algorithms;
  - Particle Swarm Optimization.

“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.
  - **Mutation Analysis**
    - **Test Case**: Target the detection of individual faults.
    - **Test Suite**: Target the detection of multiple faults of entire class/system.
  - **Code Correctness**
    - **Test Case**: Evaluate the behavior of individual instructions.
    - **Test Suite**: Evaluate the behavior of individual test cases of entire class/system.

Local Search

- ✧ Generate and score a potential solution.
- ✧ Attempt to improve by looking at its **neighborhood**.
  - Make small, incremental improvements.
  - Evaluate if solutions in the neighborhood are closer to the goal.
  - Search is directioned to adjacent areas.
- ✧ Very fast, efficient if good initial guess.
  - Get “stuck” if bad guess.
  - Often include reset strategies as search tends to get stuck.

Exploring the Neighborhood

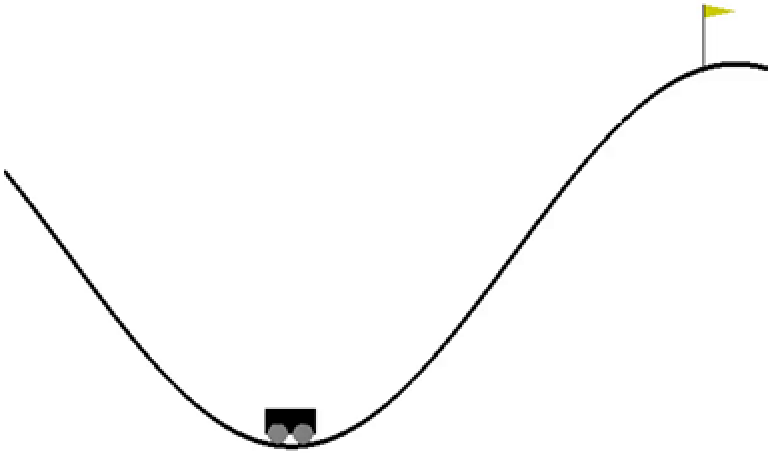
- ✧ Small changes to solution.
  - ▪ For each call:
    - Switch value of boolean, other values from an enumerated set, bounded range of numeric choices.
  - ▪ Full test case:
    - Insert a new call.
    - Delete or replace an existing call.
      - Can replace by changing the function called or its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

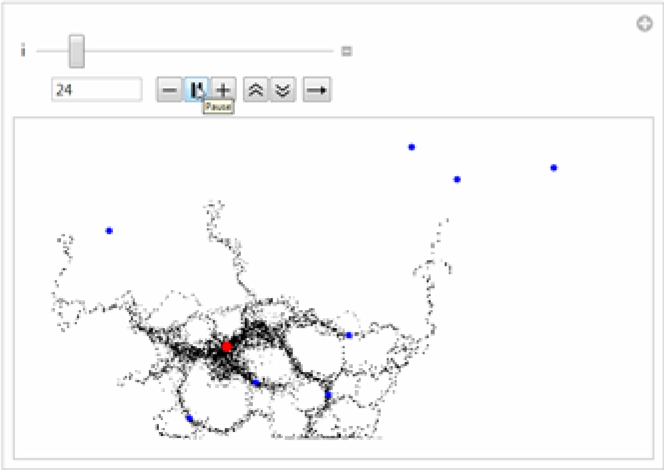


Simulated Annealing

- 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.

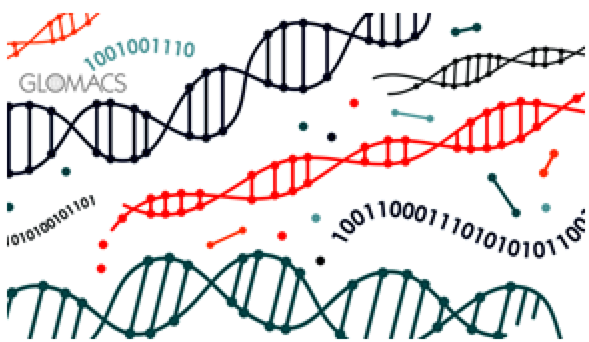
Global Search

- 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.



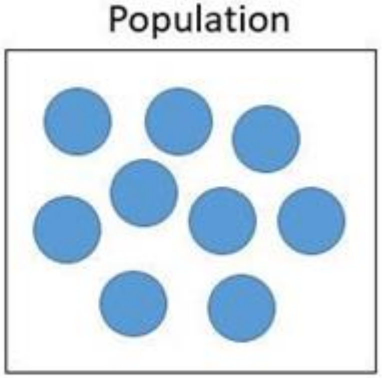
Genetic Algorithms

- Over multiple generations, evolve a population.
  - Good solutions persist and reproduce.
  - The worst solutions are eliminated.
- Diversity is introduced by:
  - Keeping the best solutions and some bad solutions.
  - Creating “offspring” through **crossover** and **mutation** to introduce genetic variety.
  - Populations with only the best solutions are not desired due to the lack of genetic diversity.



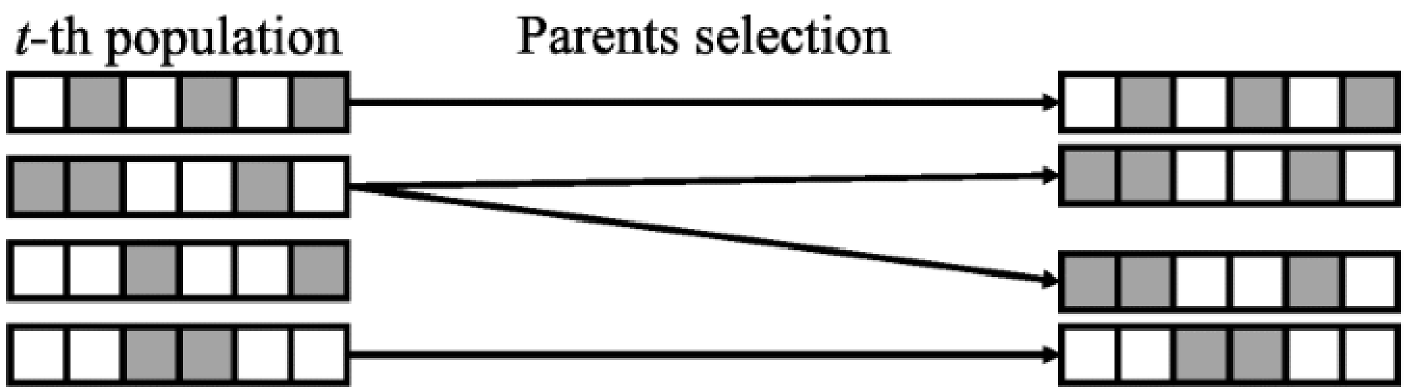
Genetic Algorithms - Population

- ✧ Set of individuals that represent possible solutions to a goal.
  - Individuals are constituted by genes which correspond to their genetic information;
  - In tests, the genes are the instructions.
- ✧ Population size remains static during the generations.
- ✧ Individuals are initialized randomly.



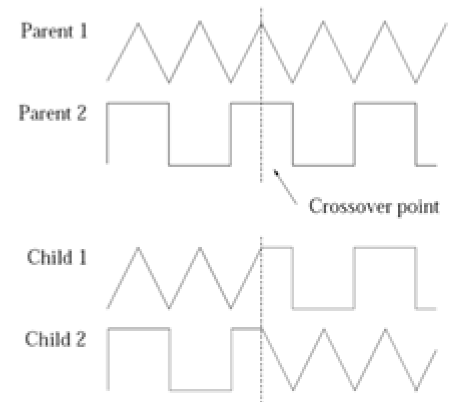
Genetic Algorithms - Selection

- Selection of the best individuals according to a goal.
- Fitness function aids this selection process.
- *N*-Individuals are chosen for the recombination process.



Genetic Algorithms - Crossover

- Exchange of information between individuals.
- Creation of two new solutions called “Offsprings".
- Crossover is based on probability.
  - Each gene can or cannot be exchanged between parents.



- Advantages.
  - Good information can be exchanged between parents.
    - Exchange of new instructions for both tests.
    - Offsprings can be closer to achieve the goal.
- Disadvantages.
  - Risk of exchanging irrelevant or bad information between parents.
    - Test cases obtaining the same instructions.

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.

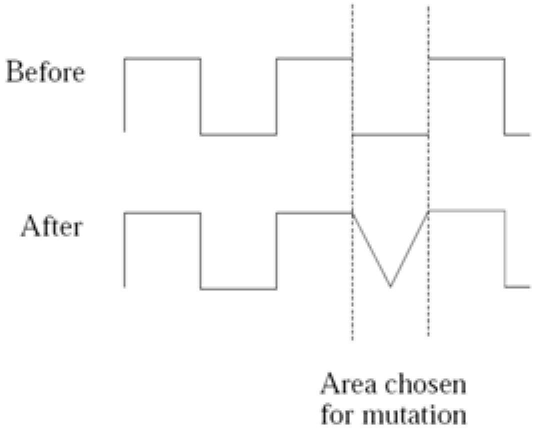
A	B	C	D		A	2	3	D
1	2	3	4		1	B	C	4

- 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

Genetic Algorithms - Mutation

- Offsprings suffer mutation on their genes.
- Small changes on the individual’s genetic information.
  - Add/delete/modify a function call;
  - Change an input value.
- Creation of two new offsprings
- Mutation is also based on probability
  - Each gene may or may not be altered.
- Advantages
  - Introduction of genetic variety in the individual
    - New instructions added or irrelevant instructions are removed.
- Disadvantages
  - Removal of genetic diversity in the individual
    - Same instructions added or removal of relevant instructions.



Genetic Algorithms - Mutation

- Bitwise
  - Bit flip of a gene.

Chromosome	1 0 **1** **0** 0 0 0 **1** 0
Mutated chromosome	1 0 **0** **1** 0 0 0 **0** 0

- Interchanging
  - Two random genes are interchanged

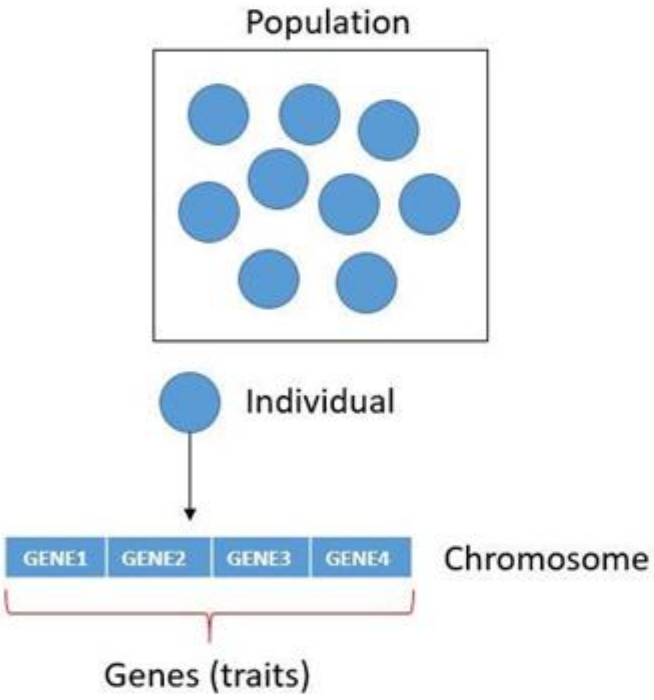
Chromosome	1 **0** 1 1 0 **1** 0 1
Mutated chromosome	1 **1** 1 1 0 **0** 0 1

- Reversing
  - Random gene is chosen and all the remaining genes after it are reversed between each other.

Chromosome	1 0 1 1 0 1 **0** **1**
Mutated chromosome	1 0 1 1 0 1 **1** **0**

Genetic Algorithms - Individuals Representation

- Representation scheme is needed for the individuals.
- The solutions have different nomenclatures for their representation
  - Phenotypes: solutions under the problem context (how a tester sees it);
  - Genotypes: encoding form under the problem context (how a computer understands it).
- The encoding scheme is limited to the problem domain.
- The binary encoding scheme is commonly used.
- Test case is the individual while genes are the instructions or test suite is the individual while genes are the test cases.



Genetic Algorithms - Termination Criteria

- Algorithms cannot run forever, so termination criteria needs to be defined.
- Genetic algorithms define these criteria according to time and solution’s evaluations
  - Maximum number of generations;
  - Time budget;
  - Best fitness score stagnation;
  - Maximum number of fitness evaluations.

Genetic Algorithms - Optimization

- Not everything is perfect under a genetic algorithm run.
- Genetic mechanisms are far from perfect.
- Optimization of genetic mechanisms and attributes is possible.
- Improving the genetic algorithm structure can lead to obtaining better strategies and consecutively better solutions during the run.
- Optimization possibilities
  - **Population size**: adapting the population size during the run;
  - **Selection**: optimizing the selection of individuals to select better genetic diversity;
  - **Crossover**: adjusting the crossover rate or crossover process considering the population evolution;
  - **Mutation**: adjusting the mutation rate or mutation process considering the fitness converging behavior.

Genetic Algorithms - Optimization

- Genetic parameters can be adjusted before and after the run;
- Techniques for parameter optimization
  - **Parameter Tuning**: adjusting parameters before the run;
  - **Parameter Control**: adjusting parameters during the run.
- Adjusting the parameters after every genetic algorithm run is expensive.
- Not all possibilities are able to be tested, so parameter control is recommended.
- Types of parameter control
  - **Deterministic parameter control**
    - Adjusting parameter values without feedback from the generation.
  - **Adaptive parameter control**
    - Optimizing parameters with generation feedback.
  - **Self-Adaptive parameter control**
    - Adjusting self-encoded parameters in the chromosomes' representation scheme;
    - Technique called “evolution of evolution”.

Genetic Algorithms - Quality

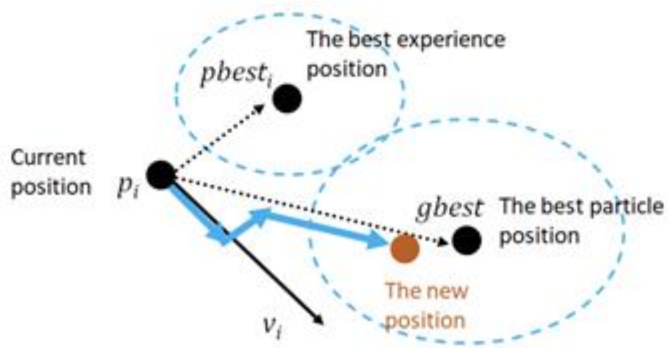
- A genetic algorithm quality can be evaluated according to three performance measures:
  - **Efficiency**: how much time the algorithm took to achieve a solution.
    - CPU or wall-clock time;
    - **Average Number of Evaluations to a Solution (AES)**: average number of fitness evaluations in a genetic algorithm run.
  - **Effectiveness**: how valuable a solution is to the predefined goal.
    - **Mean Best Fitness (MBF)**: average fitness values of the population in a genetic algorithm run.
    - **Success Rate (SR)**: percentage of runs where a desired solution was obtained.

Particle Swarm Optimization

- A swarm of agents each attempt to search for good test cases.
- When another agent finds a better solution than the best known “worldwide”, they tell everybody.
- Each agent mutates their solution based on their knowledge of the best local solution and the best global solution.
- Over time, the agents converge on the best solutions.

Particle Swarm Optimization

- Each agent has velocity and position.
  - *Position*: Their current solution.
  - *Velocity*: The amount of change to be made to the solution. Bound by a maximum velocity.
  - *Vectors* along all dimensions in the solution. (i.e., method parameters).
- Each round, velocity and position are updated based on current local and global knowledge.



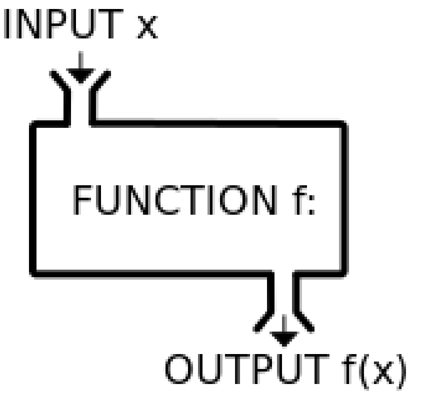
Fitness Functions

- ✧ Fitness functions play a crucial role in search-based test generation.
- ✧ Fitness functions must adhere to the following requirements:
  - Return **continuous scores** as to offer better feedback for the metaheuristic algorithms.
  - Return **only numeric values** in order to properly evaluate the generation of test cases each time.
  - Indication of how close the generation was to being optimal. It should not indicate quality but a distance to optimal quality.

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.



✧ Common fitness functions for testing

- Coverage of structural elements;
- Fault detection;
- Code correctness.

Example - Branch 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 - Branch 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 - Branch Coverage

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

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.

Goal: Branch 2, True Outcome

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 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)`

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.

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.
- Assessment of code correctness is difficult
  - Difficulty to assess which structural elements to execute;
  - Hard assessment of assertions inputs;
  - Automated generation of test oracles is still under research.

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.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