Automated Test Case Generation:

Metaheuristic Search

CSCE 747 - Lecture 22 - 04/12/2018

Testing as a Search Problem

- Do you have a **goal** in mind when testing?
- Can that goal be **measured**?
- Then you are **searching** for a test suite that achieves that goal.
  - Out of the near-infinite set of inputs, I would like a set of inputs that…
    - obey those properties.
    - cover all branches.
    - try all 2-way pairs of representative values.
    - (etc)

Testing as a Search Problem

- “I want to find all faults” cannot be checked.
- However, almost all testing goals can.
  - Boolean: Property Satisfied/Not Satisfied
  - Numeric: % Coverage Obtained
- If we can take a candidate solution and check whether it meets our goal, then computers can search for a solution.
- Many search techniques for automated test case generation.

Search Process

- Choose a solution. If it does not accomplish the goal, try another.
- Keep trying new solutions until goal is achieved or all solutions are tried.
- The order that solutions are tried is 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.

Search Budget

- Exhaustive Search - try all solutions.
- Most software has near-infinite number of inputs. We generally cannot try all solutions without constraining the problem.
- Search can be bound by a **search budget**.
  - Number of attempts made.
  - Time allotted to the search.
- **Optimization** problem:
  - Search for the best solution possible given the search budget.

Search Heuristics

- Simple strategy: randomly generate input.
  - Fast, easy to understand, very bad at finding faults.
- Adaptive random testing applies strategies to control the distribution of random test generation.
  - Retains benefits of RT, more likely to find faults.
- Dynamic symbolic execution extracts logical expressions describing program paths, and generates input from those expressions.

Search Heuristics

- Random Testing:
  - Very fast, easy to implement, requires no information about the system.
  - Unlikely to satisfy goals.
- Adaptive Random Testing:
  - Almost as efficient as RT, same other benefits, far more likely to satisfy goals. Still based on random chance.
- (Dynamic) Symbolic Execution:
  - Will find an exact solution if possible.
  - Many restrictions on complexity and data structures of the programs supported.

Optimization Problem

- Often too many restrictions to make exhaustive search feasible.
- No way to try all inputs or abstract complex systems. Instead, need a strategy to sample from the input space.
  - But not in a purely random manner.
- How can we find the best solution possible given a limited search budget?
  - Can apply optimization algorithms.
  - Called **metaheuristic search techniques**.

Metaheuristic Search

Optimization Problem

- If we can calculate a score related to attainment of a testing goal, then we have an **optimization target**.
- Test generation as an optimization problem:
  - Generate a test (or set of tests).
  - Score each of them using a **fitness function**.
  - Manipulate the solution according to a search strategy (the “**metaheuristic**”).

Metaheuristic Search

- Choose a smart strategy to sample from the search space.
  - Not purely random - fitness function guides the search towards better solutions.
  - The metaheuristic changes its approach based on past attempts.
- No guarantee of an optimal solution…
  - … but if we're smart, we'll hit something close enough.
- Computationally feasible, and often more effective than random search.

Local Search

- Generate a potential solution.
- Score it using your fitness function.
- Attempt to improve it by looking at its **local neighborhood**.
  - Test cases minorly different from the current choice.
  - Keep making small, incremental improvements.
- Very fast and efficient if you make a good initial guess.
- Can get stuck in local maxima if not.
  - Reset strategies help.

Generating Neighbors

- "Neighbors" are tests created by making a small change to the current test.
- Single method call:
  - Switch value of boolean, other values from an enumerated set, bounded range of numeric choices.
- Multiple method calls:
  - Insert a new method call.
  - Delete or replace an existing call.
    - Can replace by changing the method called or the parameters.
- Important to control size of a neighborhood.

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.
- Strategies:
  - Steepest Ascent - examine all neighbors, take the one with the highest improvement.
  - Random Ascent - examine neighbors at random, and choose the first to show any improvement.

Simulated Annealing

- Choose a neighboring test case.
  - If it is a better solution, 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
- Repeat until search budget expires and return best solution.
- Initially, large random jumps around the search space. Over time, search stabilizes.

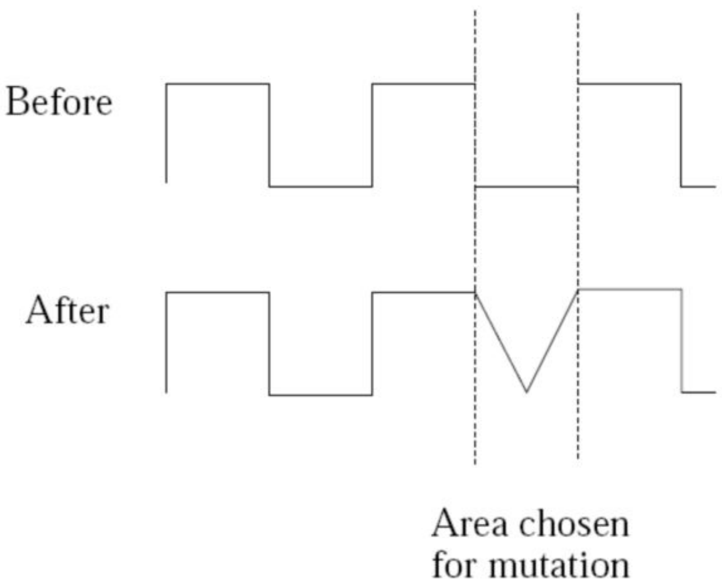
Global Search

- Generate a set of solutions.
- Score them.
- At a certain probability, sample from other regions of the space.
- Strategies typically based on natural processes - swarm attack patterns, ant colony behavior, species evolution.
  - Models of how populations interact and change.

Genetic Algorithms

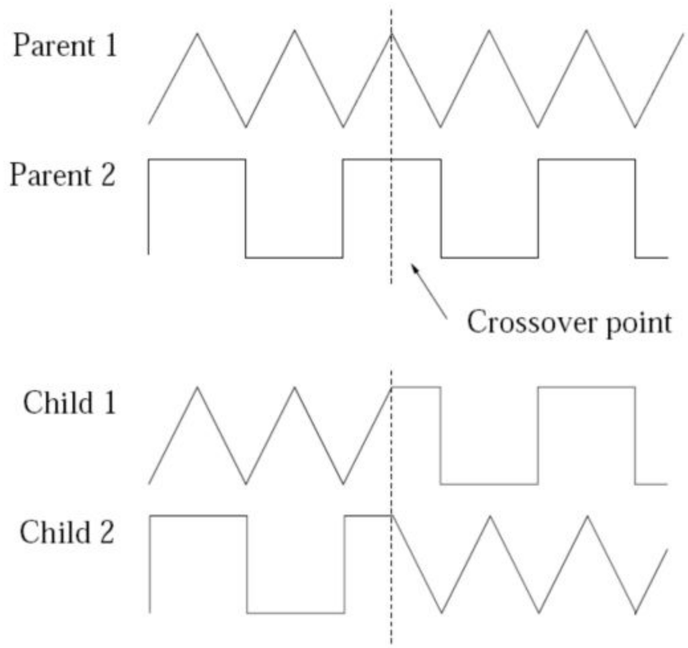
- Over multiple generations, evolve a population - favoring good solutions and filtering out bad solutions.
- Diversity is introduced to the population each generation by:
  - Keeping some of the best solutions.
  - Randomly generating some population members.
  - Creating “offspring” through mutation and gene crossover.

Genetic Algorithms - Mutation



- Create a copy of a high-scoring test.
- Impose a small change to that test.
  - Follow the rules for determining the neighbors of a test.
  - Choose a mutation from that set.
- A good test could be improved by checking one of its neighbors.

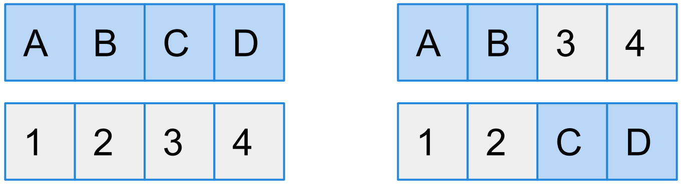
Genetic Algorithms - Crossover



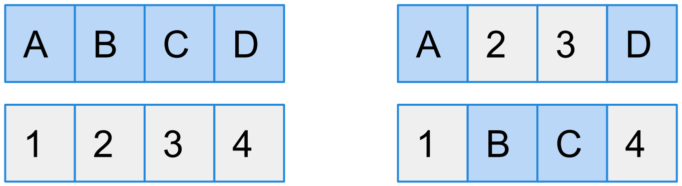
- Take two high-scoring tests, and attempt to combine aspects of them into two new tests.
- Choose one element, sample from a probability distribution to decide which parent to inherit from.
- By combining features from two good tests, we may produce a better test.

Genetic Algorithms - Crossover

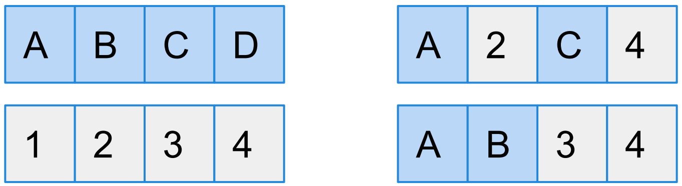
- One Point Crossover
  - Splice at a randomly chosen crossover point.



- Uniform Crossover
  - Each point is a potential crossover point.



- Discrete Recombination
  - Instead of sampling once per index for both children, it is done for for every child.



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 *i* has velocity v_i and position p_i.
  - 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.

Particle Swarm Optimization

- Update Rules:
  - $v_i^d = \omega v_i^d + \alpha\beta(best^g - p_i^d) + \gamma\delta(best^l - p_i^d)$
    - ω is an inertial weight.
      - $\omega = \omega_{max} - (\omega_{max} - \omega_{min})$ time / maxTime
      - Decreases linearly over time
    - α and γ are user-set acceleration coefficients.
    - β and δ are random numbers
    - $best^g$ is the global best score. $best^l$ is the local best score.
      - Guide the velocity and position of the agent.
  - $p_i^d = p_i^d + v_i^d$

Fitness Functions

- Solutions are judged by a “fitness function” that takes in the solution and calculates a score.
  - Distance from the current solution to the “ideal” solution.
    - How close are you to covering a testing goal?
  - Smaller scores are typically better.
  - Must offer information to guide the search.
  - Must be cheap to calculate - performed 100s-1000s of times per generation.

Structural Coverage

- Normally measured as proportion of test obligations covered to total obligations.
- This serves as a score - how good are current testing efforts.
- However, this is not an ideal fitness function.
    - Does not inform the search process.
    - Instead - can we score a test such that we can learn from the attempt?
        - Not just “is this good”, but “how close is this to ideal?”

Branch Coverage Fitness Function

- Instead of raw coverage, use the branch distance and approach level:

  fitness(s,b) = AL(s,b) + normalize(BD(s,b))

- Approach level - count of the branch's control-dependent nodes not yet executed.
- Branch distance - if the other branch is taken, measure how close the target branch was from being taken.

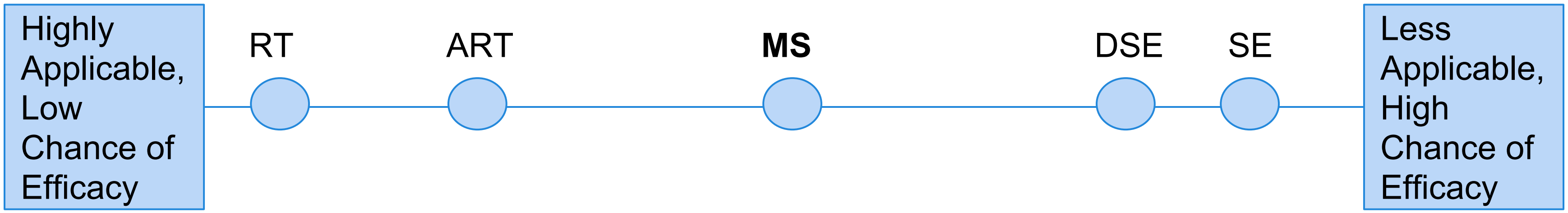
Branch Coverage Fitness Function

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

- Goal, true branch of Node 2.
- If x==10 evaluates to false, branch distance = (abs(x-10)+k).
- Closer x is to 10, closer the branch distance.

evosuite demonstration

Comparing Approaches



- Less efficient than ART.
  - But more likely to achieve the testing goal.
- Fewer restrictions than DSE.
  - But no guarantee of optimality.
- Choice of fitness function is important.
  - Must be fast to calculate.
  - Must quickly converge on optimal solutions.

Combining Approaches

```
class Foo {
    int x = 0;
    void inc(){
        x++;
    }
    int getX(){
        return x;
    }
}
```

```
class Bar{
    String x;
    Bar(String x){
        this.x = x;
    }
    void coverMe(Foo f){
      String y = x + f.getX();
      if(y.equals("baz5"))
        // target
    }
}
```

- MS can achieve high coverage, but will not guess “baz”.
- DSE can identify “baz”, but will not call Foo.inc() five times.
- By combining the two, the target can be covered.

Not Just Test Generation...

Metaheuristic search can be applied to any problem with:

- A large search space.
- Fitness function and solution generation methods with low computational complexity.
- Approximate continuity in the fitness function.
- No known optimal solution.

Automated Program Repair

- Popular projects may have hundreds of bugs reported *per day*.
- Repair techniques, like GenProg, automatically produce patches that can repair 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.
- We use the same ideas to *search* for repairs automatically.

Generate and Validate

- **Genetic programming** - solutions represent sequences of edits to the source code.
- **Generate and validate approach:**
  - Create a bunch of candidate patches.
  - Each candidate patch is applied to produce a new program.
  - See if a patched program passes all tests.
    - Fitness function: how many tests pass?
    - If tests fail, then the patch is invalid.
  - Patches that pass more tests are used to create the new population.

GenProg Results

- GenProg repaired 55 out of 105 bugs at an average cost of $8 per bug.
  - Large projects - over 5 million lines of code, 10000 test cases.
- Able to patch infinite loops, segmentation faults, buffer overflows, denial of service vulnerabilities, “wrong output” faults, and more.

Automated Code Transplantation

- Not just patches…
- Many coding tasks involve “reinventing the wheel” - redesigning and writing code to perform a function that already exists in some other project.
- What if we could slice out that code (“organ”) from a “donor” program and transplant it to the right “vein” in the target software?

muScalpel

- Uses a form of genetic programming.
- Initial population of 1 statement patches.
  - Organs need very few statements from the donor.
  - Starting with one line at a time allows muScalpel to find efficient solutions quickly.
- Search evolves both organs and veins.
  - Optimize the set of code transplanted from the donor, and the optimal location to place that code in the target software.
- Apply tests to ensure correctness of both original code and new features.

muScalpel Results

- Transplantation of encoder/decoder for H.264 video codec from x264 system to VLC media player.
  - Took VLC developers 20 days to write the code manually.
  - Took muScalpal 26 hours to transplant automatically.
- In 12 of 15 experiments, successful transplants that passed all tests.

The 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

- Tests produced by current automation are very different from human-written tests.
  - Take a “shortest-path” approach to attaining coverage.
  - Apply input different from what humans would try.
  - Execute sequences of method calls that a human might not try.
  - Apply oracles that can be trivial or incorrect.
- Automation can be very effective, but more work is needed to improve it.

We Have Learned

- ART is often ineffective, and DSE is limited in the scope of the programs it can be applied to.
- Metaheuristic search strikes middle ground:
  - Less efficient than ART, but often more effective.
  - Able to generate tests for programs that DSE cannot address.
- Smart strategies for sampling from a search space. Designed to produce near-optimal solutions within a limited search budget.

We Have Learned

- Local methods attempt to make small changes to a current solution.
  - Hill climbers, simulated annealing.
- Global methods try solutions from all around the search space.
  - Genetic algorithms, particle swarm optimization.
- Can also be used to automate patching and feature transplantation.

Next Time

- Release and Post-Release Testing
  - Chapter 22
- Homework:
  - Assignment 4 - Questions?
  - Reading Assignment 4 - April 24
    - S. Shamshiri, R. Just, J. M. Rojas, G. Fraser, P. McMinn, and A. Arcuri
    - “Do Automatically Generated Unit Tests Find Real Faults? An Empirical Study of Effectiveness and Challenges”