Applying Genetic Programming to Bytecode and Assembly

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The big picture

- Evolving whole programs is hard to do with source code.
- Evolving whole programs with bytecode and assembly is not as hard.

Outline

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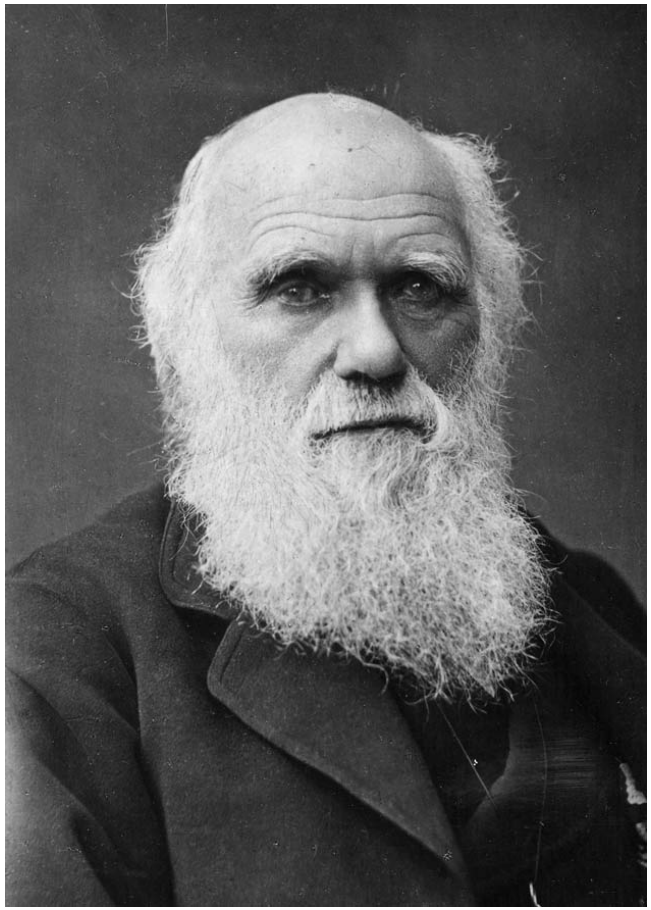
What is Evolutionary Computation?

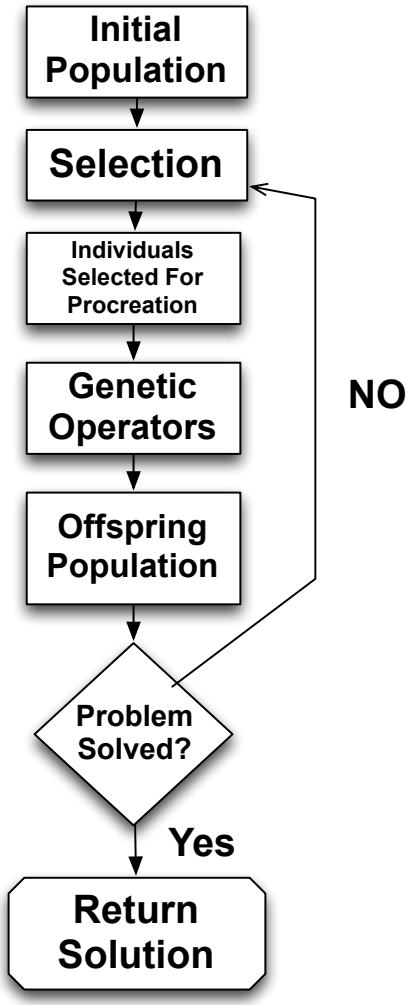
- EC is a a technique that is used to automate computer problem solving.
- Loosely emulates evolutionary biology.



Charles Darwin
http://tinyurl.com/lqwj3wt

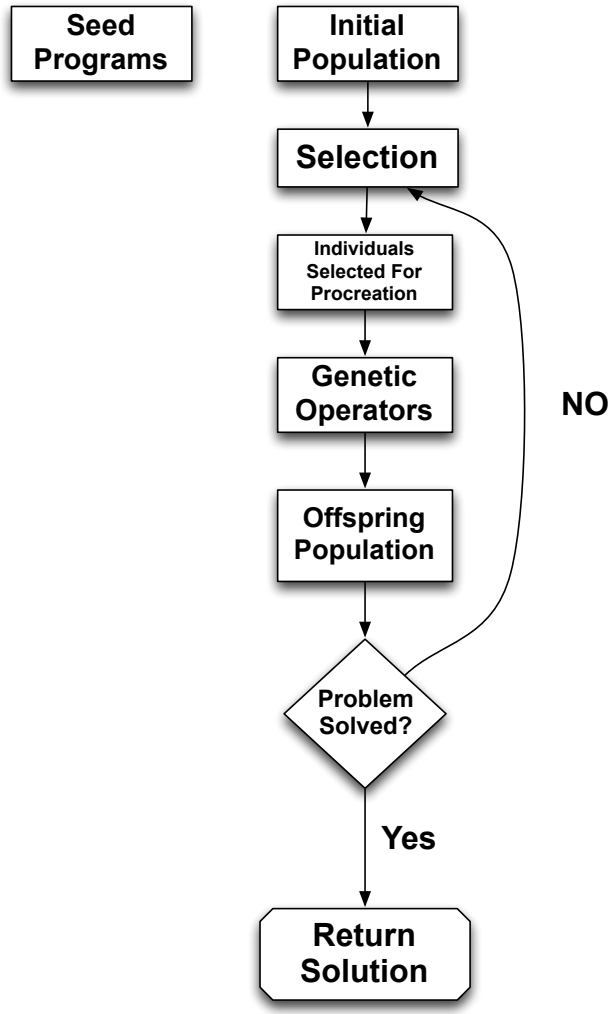
How does it work

- Continuous Optimization
- Selection is driven by the *fitness* of individuals
- Genetic Operators mimic sexual reproduction and mutation



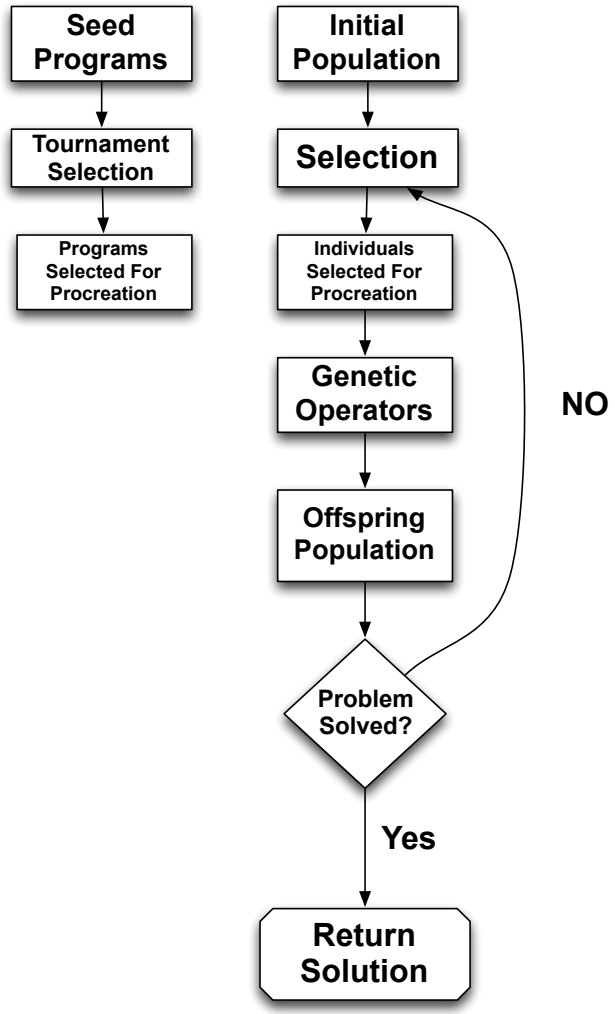
Genetic Programming

- Uses the EC technique to evolve programs
- The population is programs



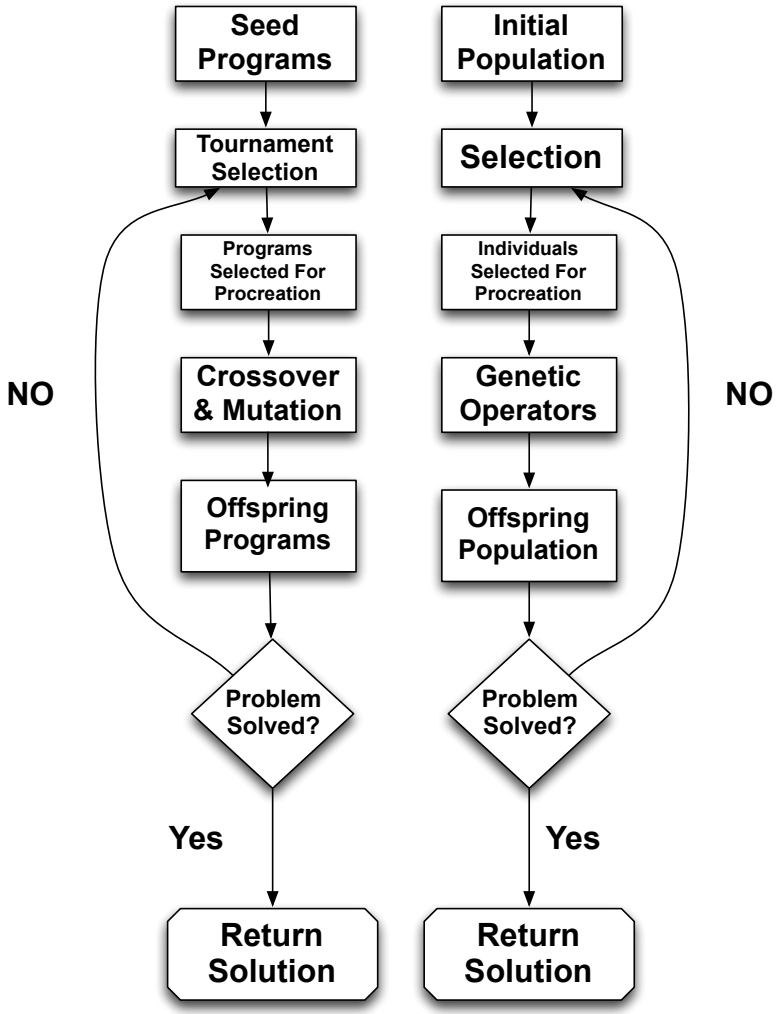
Genetic Programming

- Tournament Selection

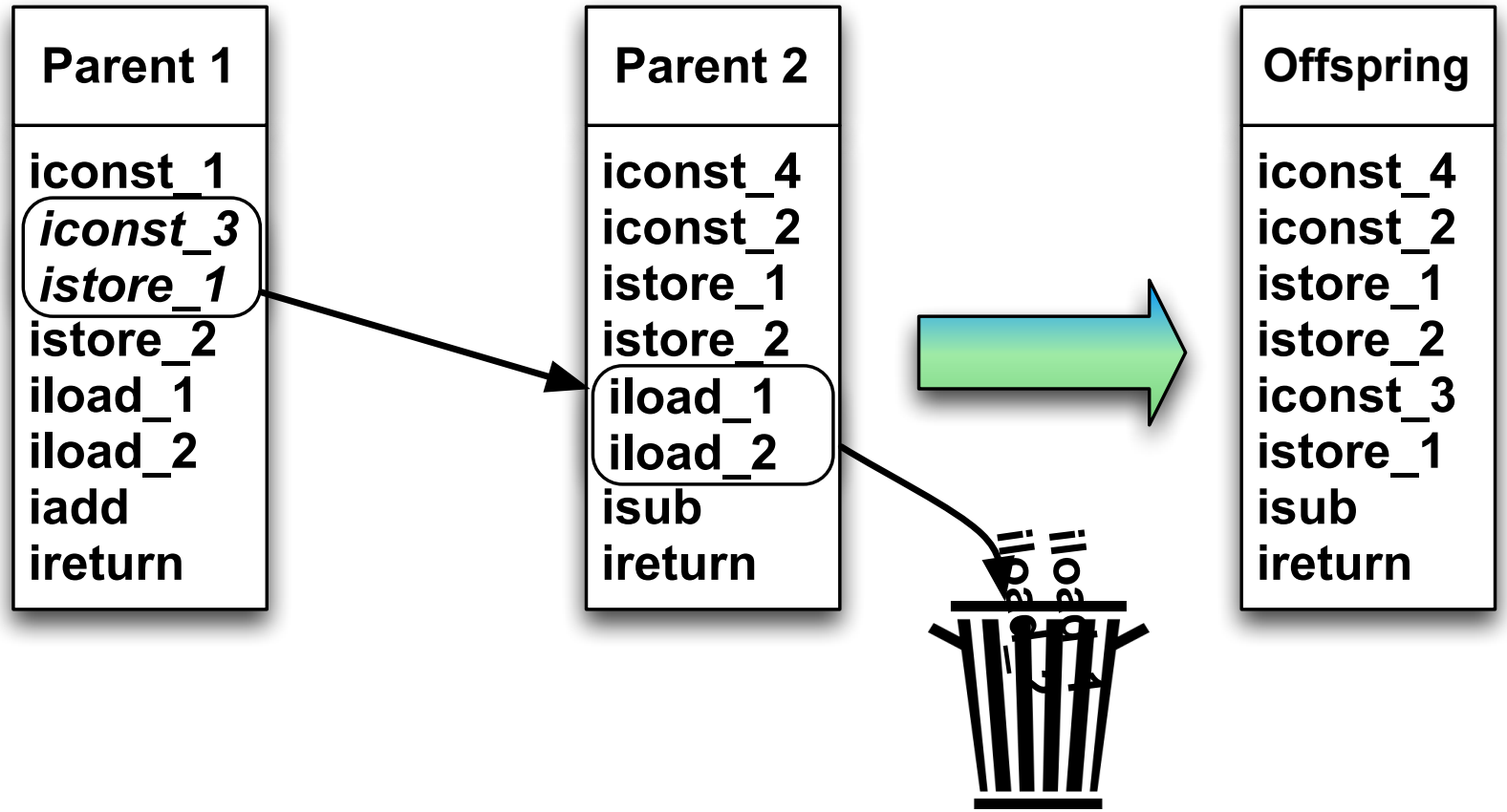


Genetic Programming

- Crossover
- Mutation

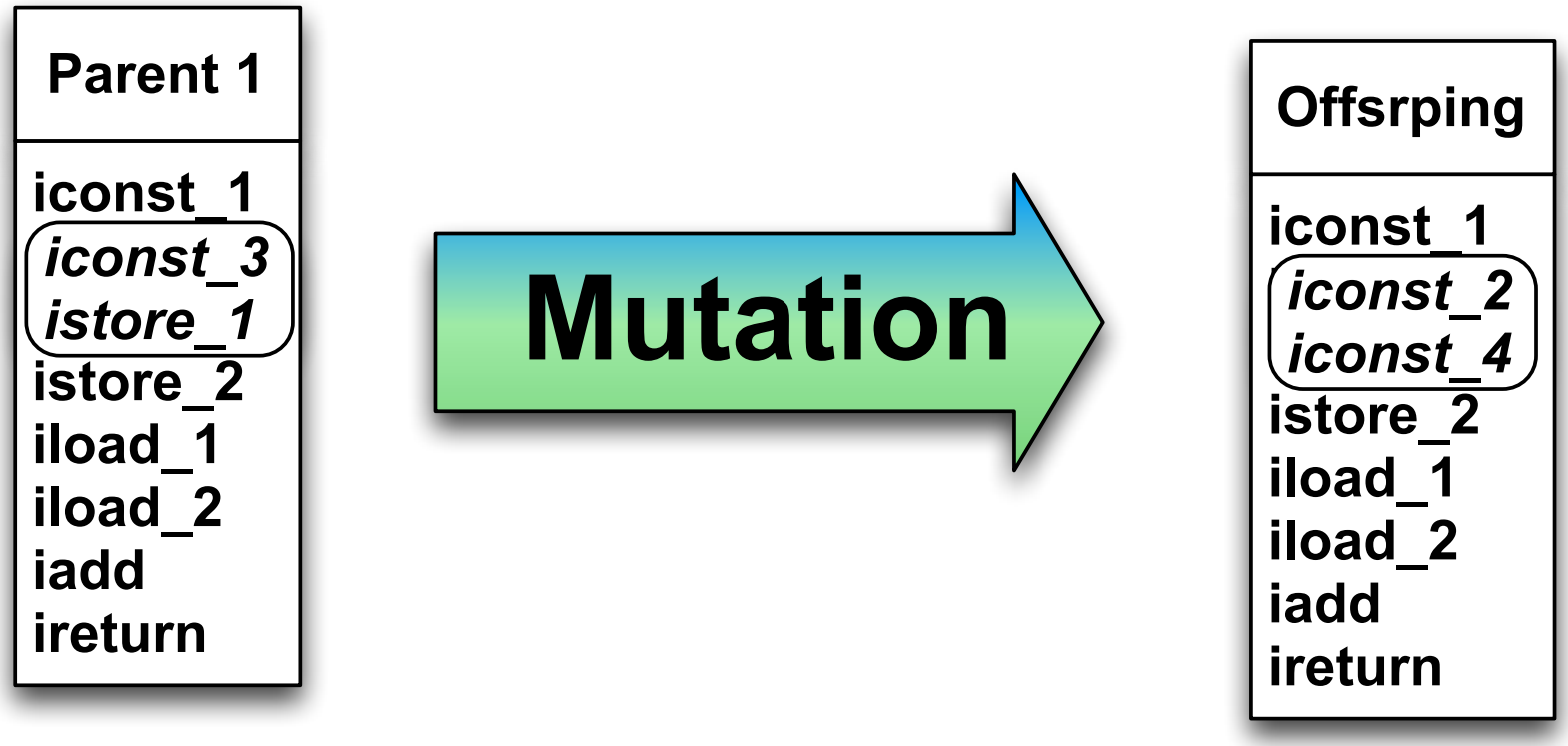


Crossover



Crossover with Java Bytecode

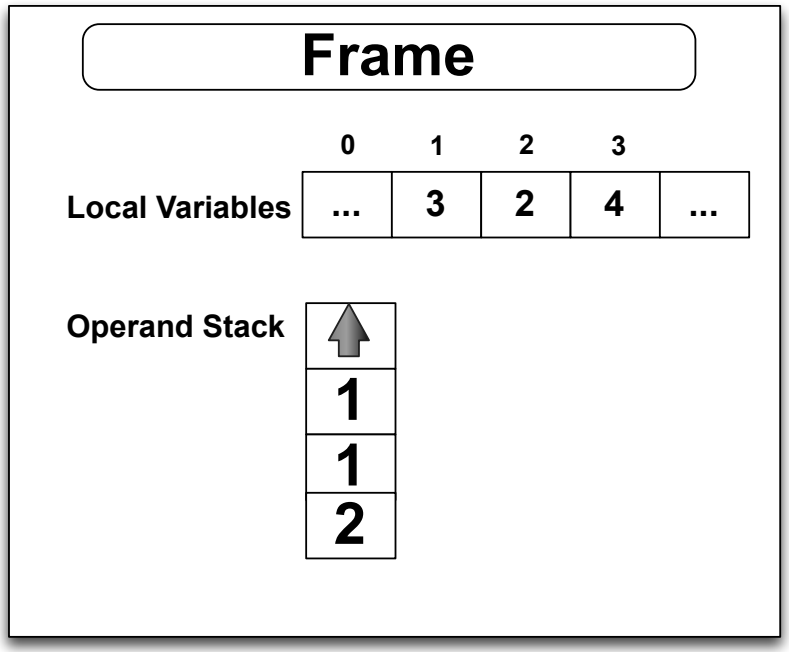
Mutation



Crossover with Java Bytecode

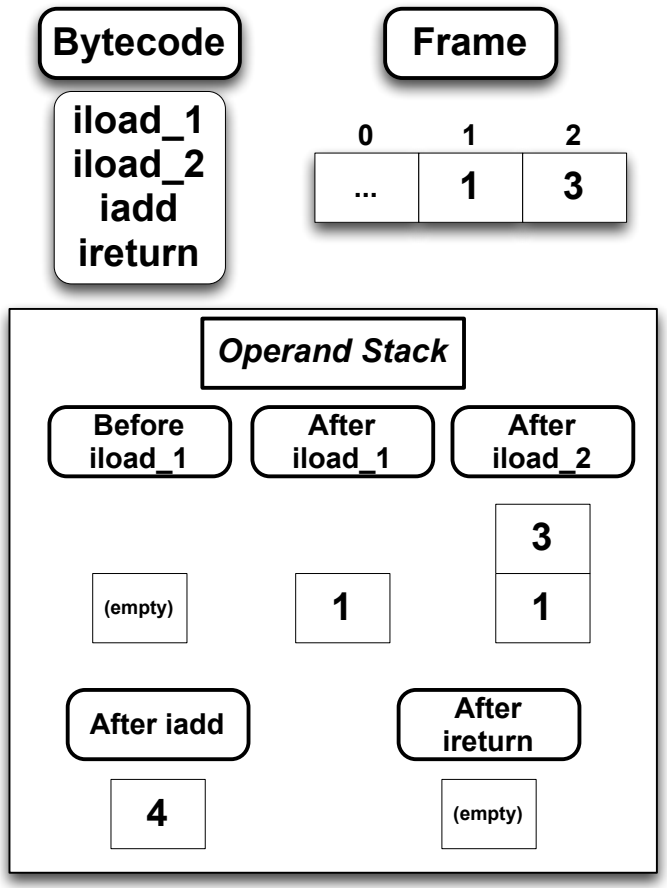
Java Virtual Machine

- Frames
- Array of local variables
- Operand Stack



Java Bytcode and Frames

- Opcodes
- Prefix indicates type



Outline

Source Code Constraints

- While it would be useful, it is difficult to apply evolution to an entire program in source code
  - Source code is made to simplify reading and writing programs
  - Source code does not represent the semantic constraints of the program.

Source Code Constraints

```
float x;  int y = 7;
if (y >= 0)
   x = y;
else
   x = -y;
System.out.println(x);
```

(a)

```
int x = 7;  float y;
if (y >= 0) {
   y = x;
   x = y;
}
System.out.println(z);
```

(b)

Both (a) and (b) are valid syntactically. However (b) is invalid semantically.

Source Code Constraints

- EAs are usually designed to avoid dealing with semantic constraints

```
class Robot{
...
  double robotSpeed(){
      double evolvedVariable = valueFromEA;
      return (robot.location + evolvedVariable)/2;
  }
...
}
```

Instruction-Level Code Constraints

- Consists of a smaller alphabets
- Simpler syntactically
- Less semantic constraints to violate

Instruction-level Code Benefits

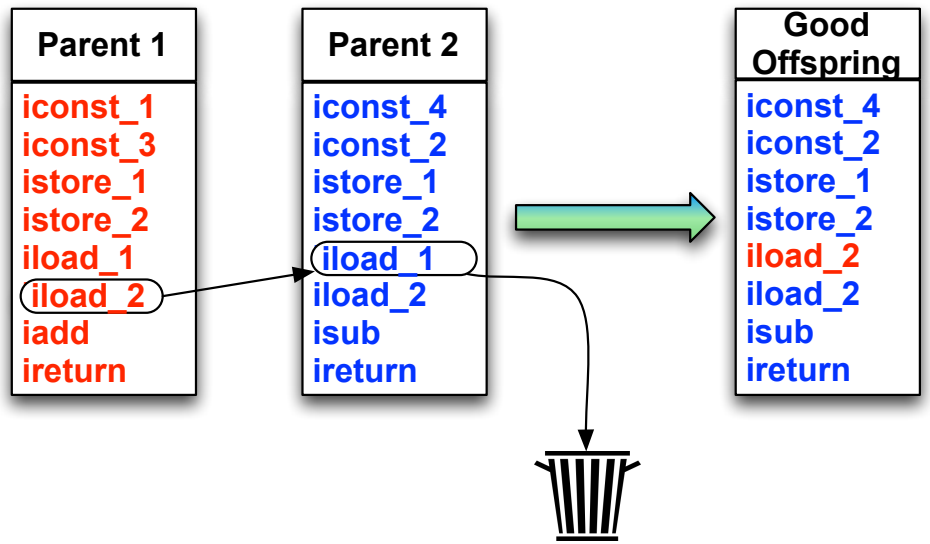
- Do not need to understand the structure of the program being evolved
- Can evolve a lot from a little
- If there is a compiler for it we can evolve it

Outline

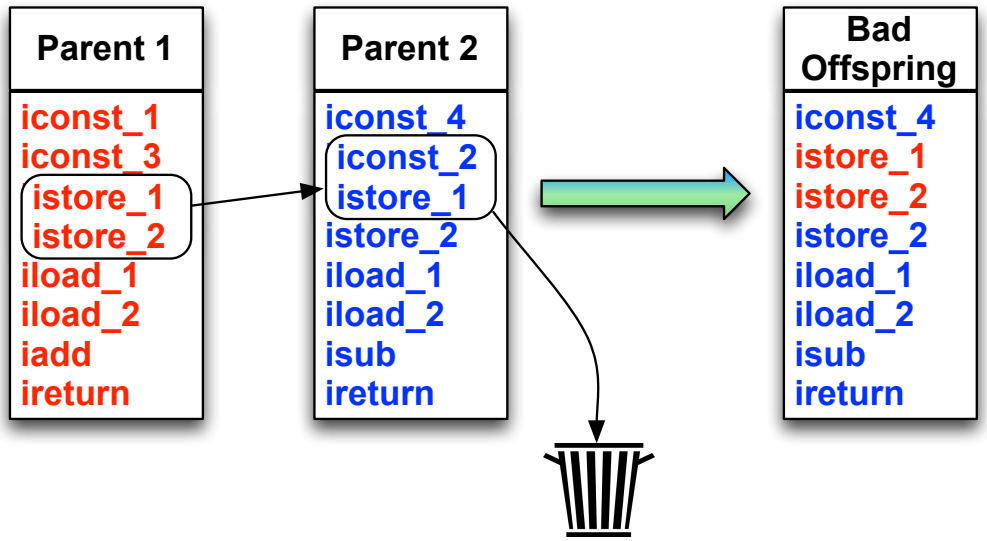
Selecting Offspring

- There is still a chance to produce non-compilable code
- Solution: add restrictions to code selection
  - Stack and Frame Depth
  - Variable Types
  - Control Flow

Good Crossover



Bad Crossover



Results

- The array sum problem
  - Started with a zero fitness seed program
  - Counted function calls to check for a non-halting state

```
int sumlistrec(List list){
    int sum = 0;
    if(list.isEmpty())
        sum *= sumlistrec(list);
    else
        sum += list.get(0)/2 + sumlistrec(
              list.subList(1, list.size()));
    return sum;
}
```

Results

```
int sumlistrec(List list) {
  int sum = 0;
  if (list.isEmpty())
    sum = sum;
  else
    sum += ((Integer)list.get(0)).intValue() +
        sumlistrec(list.subList(1,
            list.size()));
  return sum;
}
```

Outline

Selecting Offspring

- Debugging programs that consist of thousands of lines of code
- Uses a weighted path due to size of programs
- No checks if executable instruction-level code is produced

Selecting Offspring

- Each instruction is given a weight
- The weight is determined by what tests execute that instruction
- Each experiment started with one negative test case and multiple positive test cases

Non-Halting Offspring

- Only executed by failing test: weight = 1.0
- Executed by negative test and one positive: weight = 0.1
- Not executed by negative test case: weight = 0

Outline

Conclusions

References