

# Applying Genetic Improvement to MiniSAT

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# Genetic Improvement Programming



Automatically improving a system's behaviour

Non-functional properties can be the criteria for improvement

Relies on a set of test cases

Automatically improving a system's behaviour

Non-functional properties can be the criteria for improvement

Relies on a set of test cases

Genetic Programming tries many possible options

Software designer chooses best

Bowtie2:

Used for processing DNA sequences

50 000 lines of C++

DNA sequences from the “1000 Genome Project”

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50 000 lines of C++

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Only 7 lines of code changed in 3 C++ files

70+ faster on average

Very small improvement in Bowtie2 results

“Optimising Existing Software with Genetic Programming”

William B. Langdon and Mark Harman

IEEE Transactions on Evolutionary Computation

to appear

# Motivation





Try another example:

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Easy to analyse

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Easy to analyse

Popular

SAT solver:

MiniSAT

Bounded Model Checking

Planning

Software Verification

Automatic Test Pattern Generation

Combinational Equivalence Checking

Combinatorial Interaction Testing

and many others..

# Representation: Move operations



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Grammar rule:

a line of code or a part of loop/condition (for, if, while, else)

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Change code by re-using existing human written code:

Copy a line

Replace a line with another line from the program

Delete a line

Evolve a list of changes

```
<Solver_135> ::= "{Log_count64++;/*135*/} if" <IF_Solver_135> " return false;\n"  
<IF_Solver_135> ::= "(!ok)"  
<Solver_138> ::= "" <_Solver_138> "{Log_count64++;/*138*/}\n"  
<_Solver_138> ::= "sort(ps);"  
<Solver_139> ::= "Lit p; int i, j;\n"  
<Solver_140> ::= "for(" <for1_Solver_140> ";" <for2_Solver_140> ";" <for3_Solver_140> ") {\n"  
<for1_Solver_140> ::= "i = j = , p = lit_Undef"  
<for2_Solver_140> ::= "i < ps.size()"  
<for3_Solver_140> ::= "i++"
```

# Representation: Combining moves



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Mutation: append another random change to the list

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Crossover: append lists from two parents



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Crossover: append lists from two parents

Only creating a new individual shortens the list

Selection: top half of the population was chosen

# Fitness function



# Fitness function



Run program and count lines used

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2 measures:

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Quality of answers produced (right/wrong, automatic oracle)

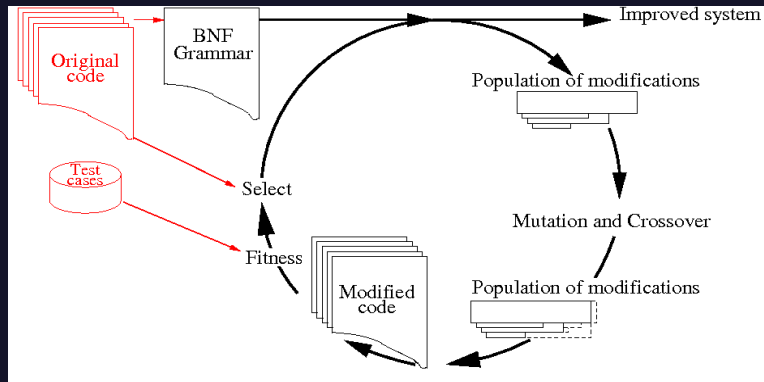
Run program and count lines used

2 measures:

Quality of answers produced (right/wrong, automatic oracle)

Resources used (number of lines used)

# GP Improvement





SAT solver

16 header files

6 C++ files

582 lines of C++ code in Solver.cc file

480 lines of C++ code in SimpSolver.cc file

BNF produces 648 lines that GP can manipulate

SAT solver

16 header files

6 C++ files

582 lines of C++ code in Solver.cc file (all experiments)

480 lines of C++ code in SimpSolver.cc file (2<sup>nd</sup> experim.)

BNF produces 648 lines that GP can manipulate

# GP evolution parameters



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Training data set size: 71

# GP evolution parameters



Training data set size: 71

Population size: 20

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Generations: 100

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Training data set size: 71

Population size: 20

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5 test examples, reselected every generation

# GP evolution parameters



Training data set size: 107 (industrial)

Population size: 100

Generations: 20

5 test examples, reselected every generation



# Results



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~ 14 hours

# Results



~ 14 hours

~ 70% compiled

# Results



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Very small improvements

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No clear winner so far..

~ 14 hours

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Very small improvements

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Mainly stats and optimisations removed

~ 14 hours

~ 70% compiled

Very small improvements (~2.5%)

No clear winner so far..

Mainly stats and optimisations removed

$$x_1 \vee x_2 \vee \neg x_4$$
$$\neg x_2 \vee \neg x_3$$

- $x_i$  : a Boolean variable
- $x_i, \neg x_i$  : a literal
- $\neg x_2 \vee \neg x_3$  : a clause



# Example



```
bool Solver::satisfied(const Clause& c) const {
    for (int i = 0; i < c.size(); i++){
        if (value(c[i]) == l_True){
            return true;
        }
    }
    return false;
}
```

# Example



```
bool Solver::satisfied(const Clause& c) const {
    for (int i = 0; 0; i++){
        if (value(c[i]) == 1_True){
            return true;
        }
    }
    return false;
}
```

# Summary



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Bowtie2 : 70+ runtime improvement

MiniSAT : very small improvements so far..



# Research directions



Specialise test sets for GP

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Change population and generation size

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Discover historical changes using an older version of the solver  
(partially done)

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Target heavily used parts of MiniSAT (partially done)

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Discover historical changes using an older version of the solver  
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Target heavily used parts of MiniSAT (partially done)

Allow to inject lines of code from other SAT solvers

Try to re-generate some functionality of MiniSAT

## The 28th CREST Open Workshop

### Genetic Programming for Software Engineering

**Date:** 14 - 15 October 2013

**Venue:** Engineering Front Executive Suite, Roberts Building, UCL (*Directions*, or 'CS' on the map *here*, or *Find it on Google maps*.)

#### Overview:

Genetic programming has found widespread application in engineering design, strategy formation, learning and modelling. More importantly for software engineering, advances in automated bug fixing, genetic improvement, program synthesis and genetic program translation have all demonstrated that GP can be used to generate usable deployed software and its components. This workshop will bring together researchers and practitioners for a two day workshop to discuss new opportunities for use of Genetic Programming for Software Engineering Optimisation.

#### Speakers:

Betty H.C. Cheng, Department of Computer Science and Engineering, Michigan State University, USA

John A Clark, Department of Computer Science and YYCSA, University of York, UK

Bill Langdon, CREST Centre, SSE Group, Department of Computer Science, UCL, UK

Claire Le Goues, School of Computer Science at Carnegie Mellon University, USA

Bob McKay, Seoul National University, Korea

Gabriela Ochoa, Computing Science and Mathematics, University of Stirling, UK

Justyna Petke, CREST Centre, SSE Group, Department of Computer Science, UCL, UK

Lee Spector, School of Cognitive Science, Hampshire College

David White, Computing Sciences, University of Glasgow, UK

John R. Woodward, Computing Science and Mathematics, University of Stirling, UK