Using Genetic Improvement to Optimise Optimisation Algorithm Implementations

Aymeric Blot Justyna Petke

University College London

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Automated Software Improvement

Software synthesis:

$$\min_{s \in S} \quad f(s,\ T)$$

With:

- s a software
- S the set of all software
- f the fitness function
- T the software specification

Genetic improvement:

$$\min_{p(s_0) \in S} \quad f(p(s_0),\ T)$$

With:

- s_0 a given software
- $p(s_0)$ a patched version of s_0

Hypothesis:

- s_0 is already very good

Genetic Improvement (GI)

Applications:

- Functional properties
  - Program repair / bug fixing
  - Feature transplantation
- Non-functional properties
  - Execution time
  - Energy / memory usage
  - Solution quality

As an optimisation problem:

- Very expensive
  - Compilation time
  - Fitness uncertainty
  - Fitness approximation
- Inconvenient search space
  - Huge neighbourhoods
  - Deceiving plateaus
  - *Fractal* nature

Motivation:

Evolve software (source code) to improve performance

Petke et al., IEEE Transactions on Evolutionary Computation, 2018

Source Code Representation

Example C++ code:

```
...
if (j > i) {
   x = j;
}
...
```

Software evolution:

- Convert source code to XML (SrcML)
- Focus on selected tags
- Mutate the AST
- Scrub XML tags

Example XML code:

```
...
<stmt>if <condition>(j &gt; i)</condition> <block>{
   <stmt> x = j;</stmt>
}</block></stmt>
...
```

Genetic Improvement (GI)

In a nutshell:

- Start from original software
- Create software mutations
- Apply, recompile, evaluate, accept
- Accumulate sequences of edits
- Show final patch

Software edits:

- Statement deletion
- Statement insertion
- Statement replacement
- Data structure replacement
- Literal mutation

Case Study

Multiobjective optimization problems with complicated Pareto sets, MOEA/D and NSGA-II (TEVC 2009)

- Simple C++ implementation
- Nine hardcoded "complicated" problems
- Inverted generational distance (IGD)

Selected files:

- `DMOEA/dmoeafunc.h.xml`
- `NSGA2/nsga2func.h.xml`
- `common/recombination.h.xml`

Li and Zhang, IEEE Transactions on Evolutionary Computation, 2009

Experimental Setup

Simple local search:

- First improvement
- Mutation:
  - 50% create/append edit
  - 50% delete edit
- Fitness:
  - CPU instructions (`perf`)
  - Reject if solution quality $> 110\%$
- Budget:
  - Wallclock time
  - ≈ 1000 evaluations

Experimental Protocol

Training: To find improved software variants

- Using the search process (local search)
- Until budget exhaustion ($\approx$ 3 hours 45 minutes)
- Three runs on one problem

Validation: To avoid overfitting

- Filter out potentially harmful mutations
- Three runs on one unseen problem

Test: To assess generalisation

- Three runs on one (new) unseen problem

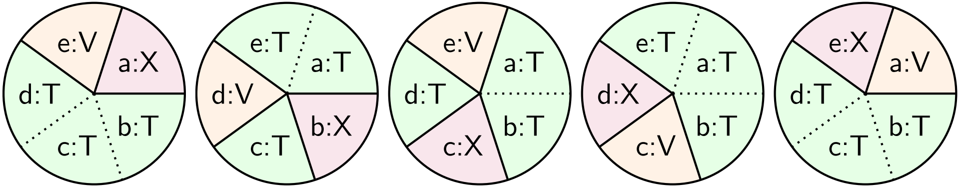
Sanity check:

- Three runs on all nine problems

Blot and Petke, Transactions on Evolutionary Computation, 2021

Cross-validation ($k = 5$)

Data is separated into k disjoint *"folds"*
Then labelled in k different ways:



Test: (X)

- Single fold
- Sequentially

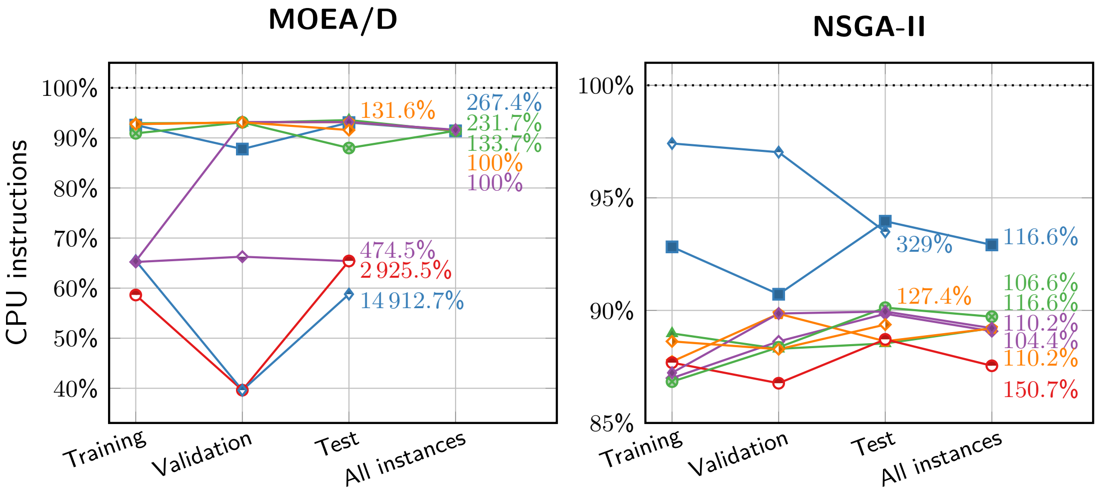
Validation: (V)

- Single fold
- Uniform at random

Training: (T)

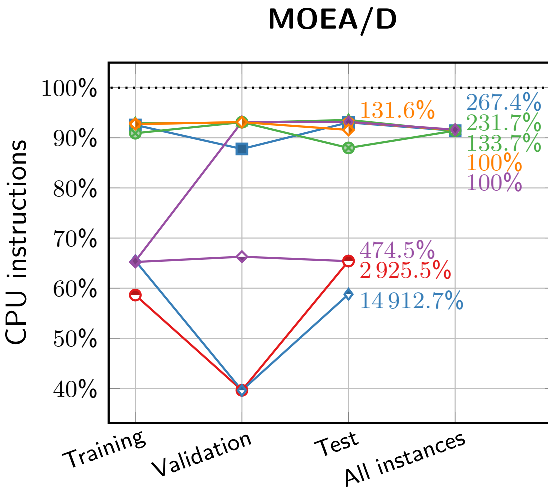
- $k - 2$ folds
- All remaining

Results



MOEA/D
NSGA-II
CPU instructions
100%
90%
80%
70%
60%
50%
40%
95%
85%
Training
Validation
Test
All instances
131.6%
267.4%
231.7%
133.7%
100%
100%
474.5%
2 925.5%
14 912.7%
329%
116.6%
127.4%
106.6%
116.6%
110.2%
104.4%
110.2%
150.7%

Results



Observations

- Consistent -7 to -12% improvement
- Major speedups (up to -60%) fail to generalise
- Various *negative* impact on solution quality

Patch Examples

Removing IGD computation: (-12% execution time at validation)

```
+++ after: DMOEA/dmoeafunc.h
 void CMOEAD::calc_distance() {
     distance = 0;
-    for(int i=0; i<ps.size(); i++) {
-        double min_d = 1.0e+10;
-        for(int j=0; j<population.size(); j++) {
-            double d = dist_vector(ps[i].y_obj,
-                                   population[j].indiv.y_obj);
-            if (d<min_d) min_d = d;
-        }
-        distance += min_d;
-    }
     distance /= ps.size();
 }
```

Patch Examples

Removing IGD computation: (-12% execution time at validation)

```
+++ after: DMOEA/dmoeafunc.h
        // load the representative Pareto-optimal solutions
        sprintf(filename,"PF/pf_%s.dat",strTestInstance);
-       loadpfront(filename,ps);
```

```
+++ after: DMOEA/dmoeafunc.h
        // load the representative Pareto-optimal solutions
-       sprintf(filename,"PF/pf_%s.dat",strTestInstance);
        loadpfront(filename,ps);
```

Note:

- Final population was captured and externally reassessed

Patch Examples

Hidden parameter tuning: (-48% execution time at validation)

```
+++ after: DMOEA/dmoeafunc.h
            // mating selection based on probability
            if (rnd<realb)   {type = 1;} // neighborhood
-           else             {type = 2;} // whole population
+           else             {}    // whole population
```

Notes:

- Brackets added automatically thanks to SrcML
- `realb` $= 0.9$
- Failed to generalise on third problem (test)

Patch Examples

New strategy: (-27% execution time at validation)

```
+++ after: DMOEA/dmoeafunc.h
                // produce a child solution
                CMOEADInd child;
                diff_evo_xover2(population[n].indiv,
                                population[p[0]].indiv,
                                population[p[1]].indiv,
                                child);
+               type = 1;
                // apply polynomial mutation
                realmutation(child, 1.0/nvar);
```

Notes:

- type is used twice (`matingselection(...)` and `update_problem(...)`)
- Insertion happens between both uses
- Fail to generalise on third problem (test)

Patch Examples

New strategy: (-9% execution time at validation)

```
+++ after: NSGA2/nsga2func.h.xml
      bool flag = true;
      int  size = offspring.size();
-     for (int i=0; i<size; i++) {
-         if (ind==offspring[i]) {
-             flag = false;
-             break;
-         }
-     }
+     nfes    = 0;
      if(flag) offspring.push_back(ind);
```

Notes:

- Remove duplicity check (reset debug variable)
- Generalises, but worse fitness ($+50\%$) during sanity check

Conclusion

Findings:

- "Free" 10% speedup
- Algorithmic changes
  - Some "known"
  - Some "new"
- Overfitting issues

What's next?

- Better multi-objective setup
- New targets for edits
- Transplantation from optimisation frameworks
- Guidance process

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Take Away

To err is human

- Practice $\neq$ theory
- Software bugs and defects

Automated performance improvement

- Compiler/parameter tuning
- Source code evolution (with GI)

Genetic improvement

- Evolution applied to software
- Functional properties
  - Bug fixing
  - Functionality transplantation
- Non-functional properties
  - Execution time
  - Solution quality
  - Energy/memory usage

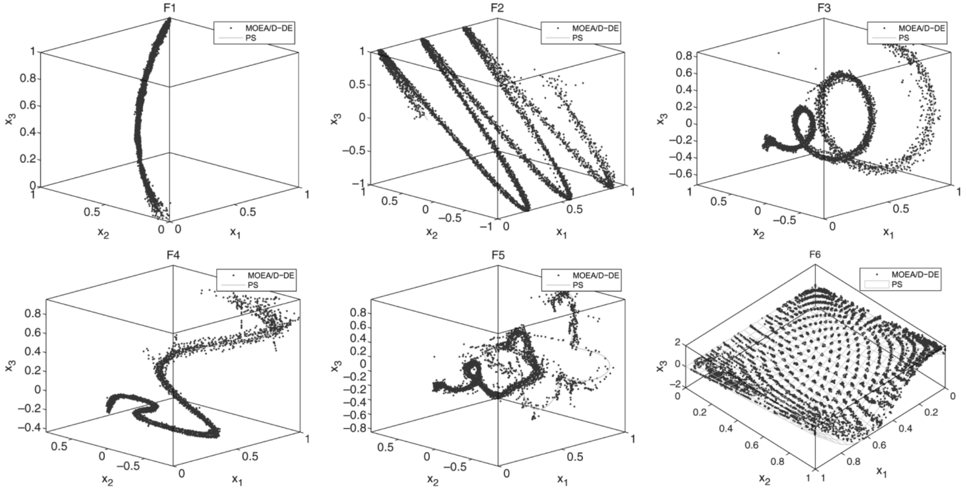
Selected References

Aymeric Blot and Justyna Petke.
Empirical comparison of search heuristics for genetic improvement of software.
IEEE Transactions on Evolutionary Computation, 25(5):1001–1011, 2021.

Hui Li and Qingfu Zhang.
Multiobjective optimization problems with complicated Pareto sets, MOEA/D and NSGA-II.
IEEE Transactions on Evolutionary Computation, 13(2):284–302, 2009.

Justyna Petke, Saemundur O. Haraldsson, Mark Harman, William B. Langdon, David R. White, and John R. Woodward.
Genetic improvement of software: A comprehensive survey.
IEEE Transactions on Evolutionary Computation, 22(3):415–432, 2018.

Complicated Pareto Sets (MOEA/D)



Li and Zhang, IEEE Transactions on Evolutionary Computation, 2009