Long-Term Stability of Genetic Programming Landscapes


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Technical report RN/17/05
https://arxiv.org/abs/1703.08481

Video1
Video2
Genetic Programming and Long-Term Evolution Experiments

• Why we care about LTEE
• Evolving Bacteria 60,000 generations v. evolving programs 100,000 generations
• LTEE continuous innovation v convergence
• Existing results on landscape of large trees
• New results
  – Increase in code (bloat), end of bloat
  – Theory some true, some less so
  – Evolution has smoothed large tree landscape although fitness distribution remains rugged.
Why Long Term Evolution Matters

• More challenging problems may require running evolution for longer.
• Hence the need to study what happens in long runs.
• By mapping landscape far from origin, perhaps we can anticipate and solve problems that may occur.
Long-Term Evolution Experiment

Mean fitness of nine E. coli populations from the LTEE

Evolving Bacteria 60,000 generations
Even after 60,000 gens fitness still improving

Convergence of Fitness Distribution

Large tree fitness distribution remains rugged like small trees but as we will see GP population maintains smooth landscape
Genetic Programming and Long-Term Evolution Experiments

• GP system able to run thousands of generations. (Do not stop when solved)
  – Expect bloat (tree growth)
  – Compact representation of trees
  – Fast fitness evaluation
    • GPquick C++, written by Andy Singleton
      ≈ two bytes per tree node

• Submachine code genetic programming
Evolution of Program Size

Note evolution continues after 1\textsuperscript{st} solution found in generation 22 and even after 1\textsuperscript{st} population when everyone has maximum fitness (generation 312).

GP+EM (1)1 pp95-119
Evolution of Program Size

Note evolution continues even after 1\textsuperscript{st} population when everyone has maximum fitness (generation 312) but tree size falls as well as rises.
Theory \[ y = 2 \text{popsize}(1-(1-x/\text{popsize})^7) \] matches experiment
6-Mux Fitness Convergence

Plot smoothed by taking running average over 30 generations

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Convergence in Genetic Programming

• GP genotypes do not converge. Even after many generations every tree in the population is different, BUT…

• Every (or almost all) trees give the same answers (phenotypic convergence)

• Effective code, i.e. code to solve problem, does converge.

  Effective code other runs converges differently
Convergence of typical Effective Code

Gen 400
Only 111 instructions of 15,495 are effective

Gen 500
Only 141 instructions of 16,831 are effective

Tree drawing code lisp2dot.awk
Convergence of Effective Code

6-Mux (binary tree) population at generation 100

Effective code only. Yellow highly converged. Black unique code

Circular lattice code gp2lattice.awk
Both whole trees and subtrees lie near the Flajolet Depth $\approx 2 \left( \frac{\pi \text{size}}{2} \right)^{\frac{1}{2}}$ limit for random trees.
Bloat limited by Gambler’s ruin

• Tiny fraction of disrupted (low fitness) children sufficient to drive evolution towards ever bigger trees.
• As trees get bigger chance of hitting protected effective code near root node falls.
• In a finite population eventually no child will be disrupted.
• Size, without fitness, wanders at random.
• But wondering towards lower limit will re-establish the conditions for bloat.
  cf. Gambler’s ruin.
• Very approximate limit on tree size:
  tree size \approx \text{number of trees} \times \text{core code size}
Bloat limited by Gambler’s ruin

Mean size (millions). Ten runs, population 50 trees

- tree size $\approx$ number of trees $\times$ core code size
- tree size $\approx 50 \times 497 \approx 25\,000$
- Across ten runs and 100,000 generation, median mean size $42\,507$ (smallest tree in pop size=10,513)

In all ten runs the whole population repeatedly collapses towards smaller trees
Conclusions

- Studied long term evolution (>>any other GP)
- 100s gens where everyone has same fitness
- No selection to drive size increase
- Gambler’s ruin with size falling as well as rising
- Evolved effective code surrounded by ring of sacrificial constants and introns
- Trees and subtrees resemble random trees
- Landscape looks smooth but fitness is rugged
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END

http://www.cs.ucl.ac.uk/staff/W.Langdon/  http://www.epsrc.ac.uk/
Genetic Programming

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GPquick

• GPquick C++, written by Andy Singleton
  ≈ two bytes per tree node

• Submachine code GP
  – Boolean (bit) problems.
  – AND, NAND, OR, NOR operate simultaneously in parallel on bits in word (e.g. 32 or 64 bits)
  – 64 bit computer can do 64 test cases in parallel
6 Multiplexor

- GP bench mark.
- Six inputs:
  - Use two (D4 D5) as binary number to connect corresponding data lines (D0-D3) to the output
- Test on all $2^6 = 64$ possible combinations
- Fitness score (0-64) is number correct
Genetic Programming to solve 6-Mux

- Terminals (tree leafs)
  - D0, D1, D2, D3, D4, D5

- Function set: 2 input gates → binary trees
  - AND, NAND, OR, NOR. No side effects

- Generational population of 500 trees

- Tournament selection: choose best of 7

- 100% subtree crossover

- Initially hard limit on tree size (10^6)

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Impact of Subtrees

- Subtree like whole tree.
- Output of subtree is via its root node.
- **Intron**: subtree which has no effect on overall fitness. I.e. its output does not impact on root node of whole tree.
- **Constant** subtree always has same output, i.e. same output on all 64 test cases.
- Remaining **effective code** has an impact on root node. Typically it is next root node.
Example Intron: AND Function

Left: two input AND node.
Right: same but input B is always 0.
So output always 0. Input A has no effect.
Subtree A is always ignored, even in child.
(NB no side effects)
Constants

• Two constants: always 0 and always 1 (FFFFFFFFFFFFFFFF).

• E.g. evolve by negating input and ANDing with same input
  \[(\text{AND D0 (NOR D0 D0)}) = 0\]

• Constants help form introns but may be disrupted by crossover.

• However large subtrees which always output either 0 or 1 tend to be resilient to crossover
Runts Drive Evolution

Don’t plot ratio if less than 5 data
Importance of Mothers

All children fitness \(<64\) when both parents fit\(=64\)

Size of poor fitness children closely related to parent who they inherit root from (mum).
• Although many runts are smaller than their mum,
• many mothers of runs are smaller than average.
• Selection removes all low fitness children,
• Since these are smaller than average, the average size increases
A few runts drive size increase

- Many mothers of runts are smaller than average (blue)
- Selection removes all low fitness children (runts)
- Since these are smaller than average
- Although there is noise, on average size increases
• Theory assumes crossover only (no selection). In earlier work distribution of sizes converged to limit rapidly.
• Selection caused by a few runts modifies size distribution
Testing Theory

6-Mux 500 binary trees (run 100 up to Gen 2500)

- Same as testing theory plot but do every generation
- Colour only part of histogram $\geq 3\sigma$
- Small tree and large tree tails ok (not coloured)
The Genetic Programming Bibliography

http://www.cs.bham.ac.uk/~wbl/biblio/

11628 references, 10000 authors

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