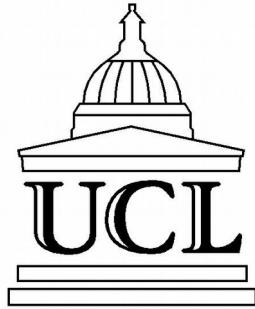


Genetic Programming Convergence

W. B. Langdon. 2022. GP & EM 23(1) 71–10

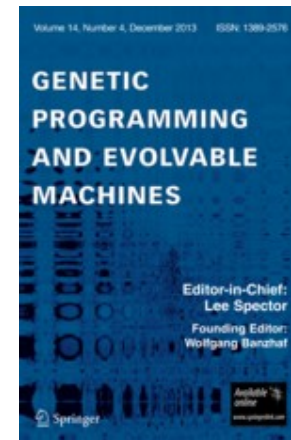
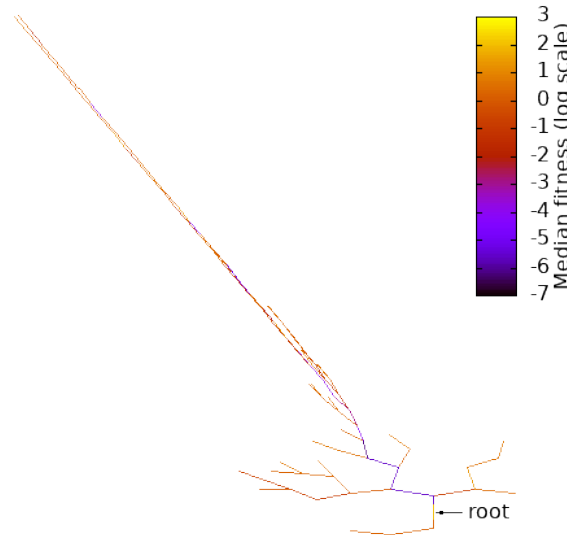
<https://doi.org/10.1007/s10710-021-09405-9>



W. B. Langdon



Sextic Polynomial Phenotype Convergence, generation 100



March 2022

Genetic Programming Convergence

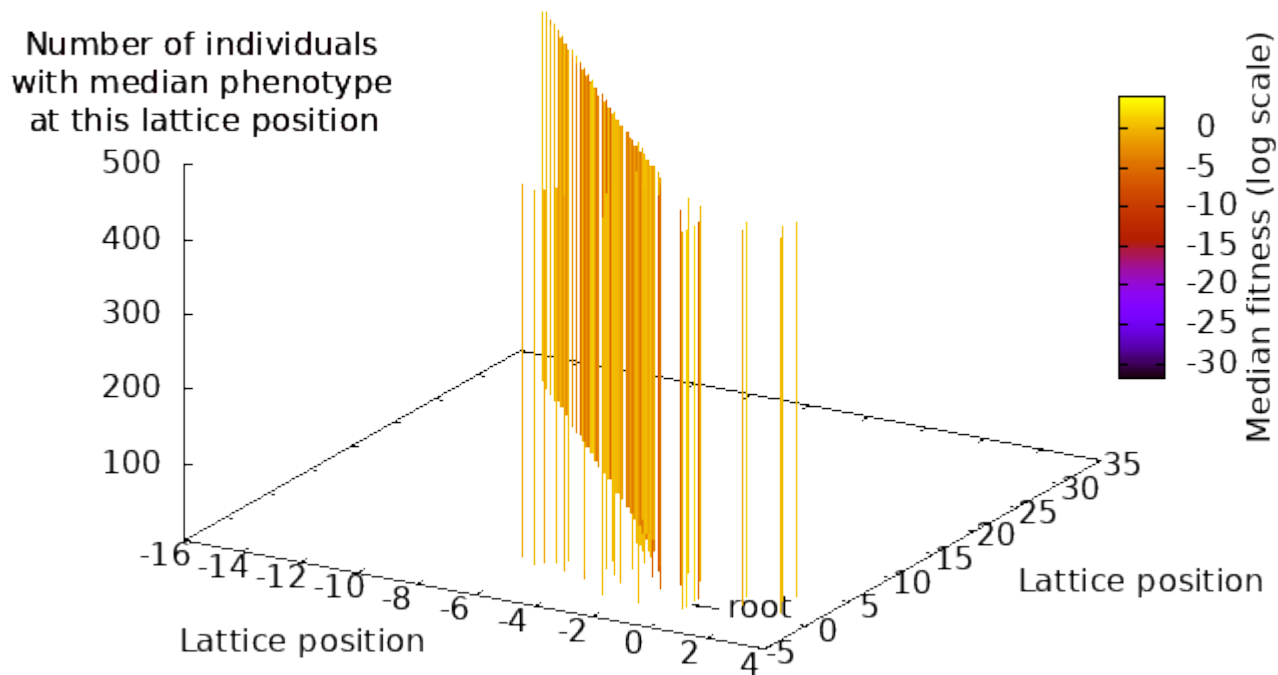
- Paper looks at symbolic regression tree over 100,000 generations.
- Evolution continues
 - Size and shape. Everyone is *unique* but
 - Convergence of fitness
 - Convergence of tree contents
 - **Convergence of tree node run time values**
 - Fraction introns 0.5% to 91%
 - Information theory applied inside GP
 - Very fast (trillion GP op/sec) fitness evaluation
 - Ideas for better crossover/mutation and representation

Convergence of tree node run time values

- Consider every node in every tree in the population
- Each is evaluated once per test case. Summarise this phenotypic information via the fitness function one value
- Every tree is *unique* but often in the population nearly all trees have a node at a given position.
- Often the contents of that node is the same in many trees
- Often the run time phenotype is the same in many trees.
- Graph height shows number of such trees. Colour gives nodes' median subfitness. Often interquartile range is zero.
- Some genetic/phenotypic variation (eg unique nodes) remains but have little impact on fitness.

Convergence of tree node run time values

Sextic Polynomial Phenotype Convergence, population 500, generation 100



10,000 generations [video's url](#)

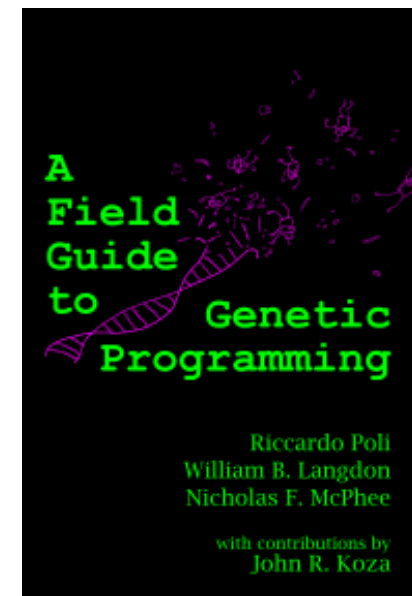
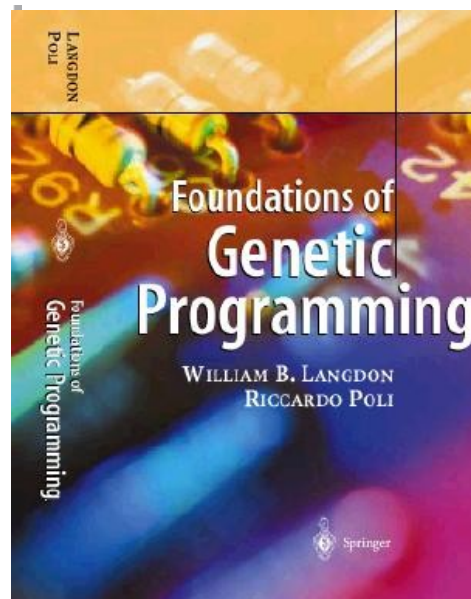
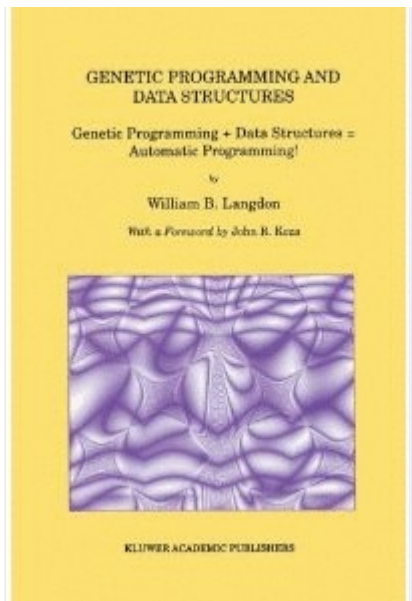
Conclusion Deep nesting hides crossover

- 1) Strong selection drives convergence despite each program in the population being unique
- 2) Because evolved trees become deeper making crossover points deeper, giving longer paths from crossover disruption site to fitness effecting root node
- 3) Information theory shows longer paths are more susceptible to failed disruption propagation. So more daughters have same fitness as their mum's.
 - Design your new crossover & mutation operators
 - Design test set (here $|x| > 1$ more effective)
 - Consider function set as information flow (division lossy)
- 4) Information loss gives smoother fitness landscape and evolution may slow but still continue

Genetic Programming



W. B. Langdon



Issues

- Exponential decay in number of disrupted test cases suggests effectiveness of test suite of n tests rises only slowly with number of tests, $\text{Log}(n)$
 - With reasonable assumption this can be proved
[Measuring Failed Disruption Propagation in Genetic Programming, GECCO 2022]
- Some mutations not being totally concealed
 - Can we characterise them?
 - Should we use them more or less in GP?
 - Can we characterise the tests needed to find them
- How much does this generalise to other types of GP
- Can lessons on mutations and testing be used in Software Engineering

The Genetic Programming Bibliography

15582 references, [15000 authors](#)

Make sure it has all of your papers!

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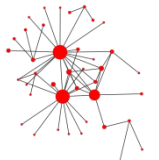


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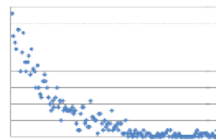
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