

### Long-Term Stability of Genetic Programming Landscapes

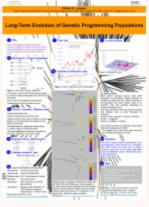
Workshop on Landscape-Aware Heuristic Search, 16 July 2017, Nadarajen Veerapen et al., GECCO-2017, Berlin, Germany. Room Diamant

### W. B. Langdon Department of Computer Science



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

Long-Term Evolution of GP Populations Poster Monday 17:50-20:00 GECCO companion p235-236







### 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.

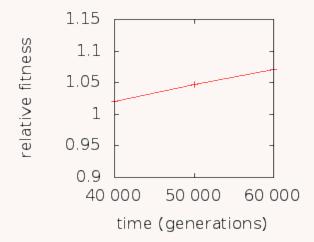


### Why Long Term Evolution Matters

- 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 60000 gens fitness still improving

Richard Lenski pulls frozen bacteria cultures out of a freezer 15 Oct 2009

R. E. Lenski *et al.* 2015. <u>Sustained fitness gains and</u> variability in fitness trajectories in the long-term evolution experiment with Escherichia coli. Proc. Royal Soc.

### Convergence of Fitness Distribution

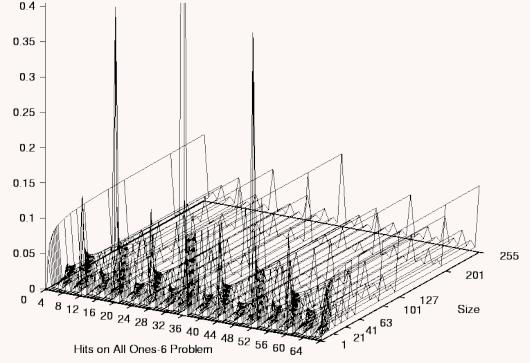


Fig. 7.7 Foundations of Genetic Programming

E S

Large tree fitness distribution remains rugged like small trees but as we will see GP population maintains smooth landscape



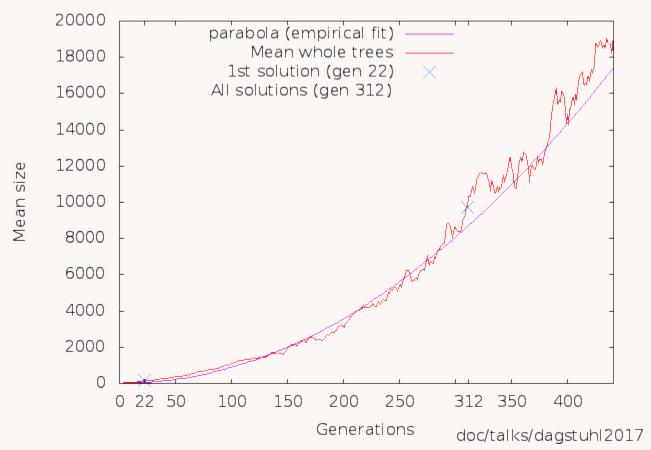
### Genetic Programming and Long-Term Evolution Experiments

- 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
- <u>Submachine code</u> genetic programming



## **Evolution of Program Size**

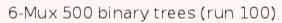
6-Mux 500 binary trees (run 100)

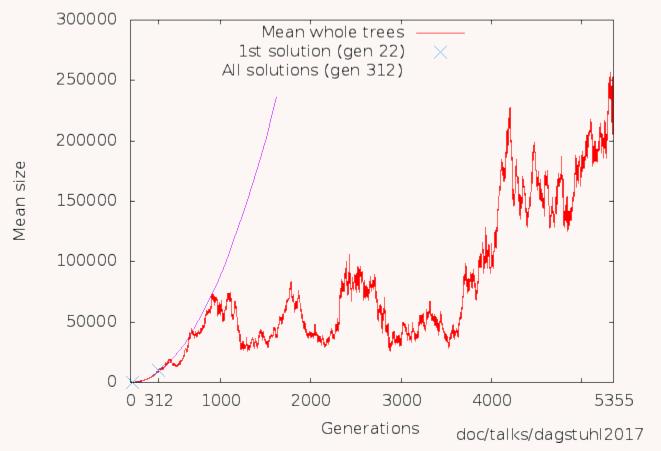


Note evolution continues after  $1^{st}$  solution found in generation 22 and even after  $1^{st}$  population when everyone has maximum fitness (generation 312). <u>GP+EM (1)1 pp95-119</u>



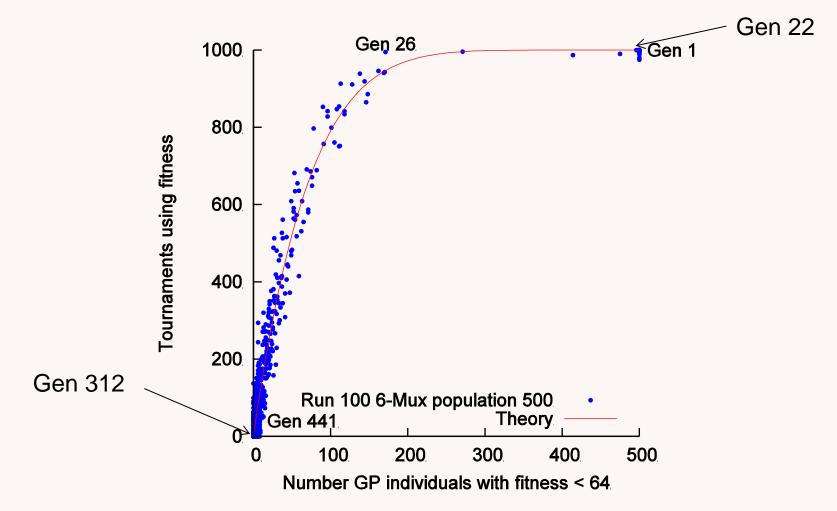
## **Evolution of Program Size**





Note evolution continues even after 1<sup>st</sup> population when everyone has maximum fitness (generation 312) but tree size falls as well as rises.

### 6-Mux Fitness Convergence



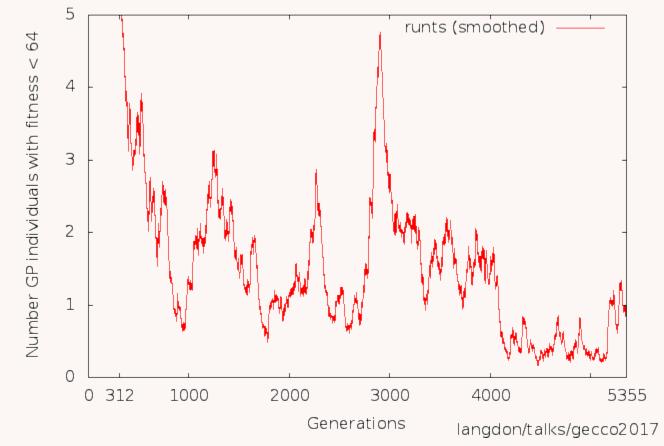
Theory  $y = 2popsize(1-(1-x/popsize)^7)$  matches experiment

REST

## 6-Mux Fitness Convergence

REST

6-Mux 500 binary trees (run 100)



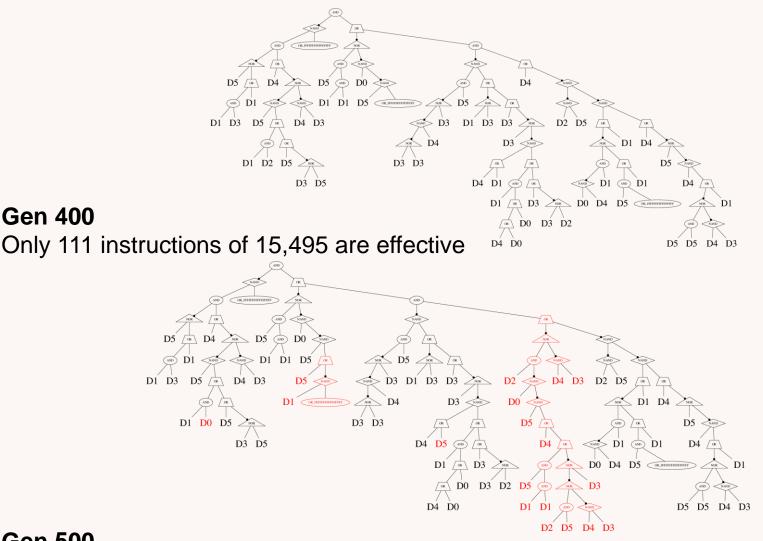
Plot smoothed by taking running average over 30 generations

# 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 500

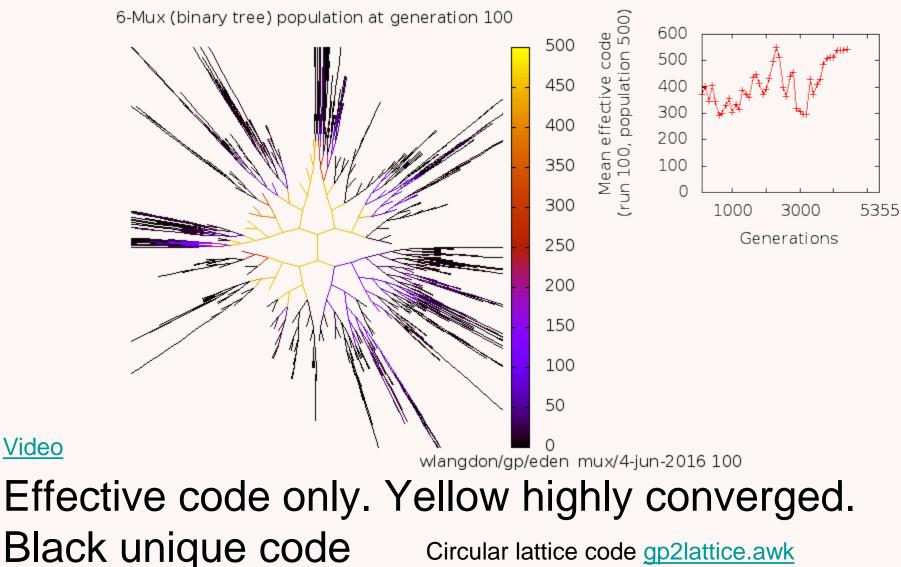
Only 141 instructions of 16,831 are effective

Tree drawing code <u>lisp2dot.awk</u>

## **Convergence of Effective Code**

REST

<u>Video</u>



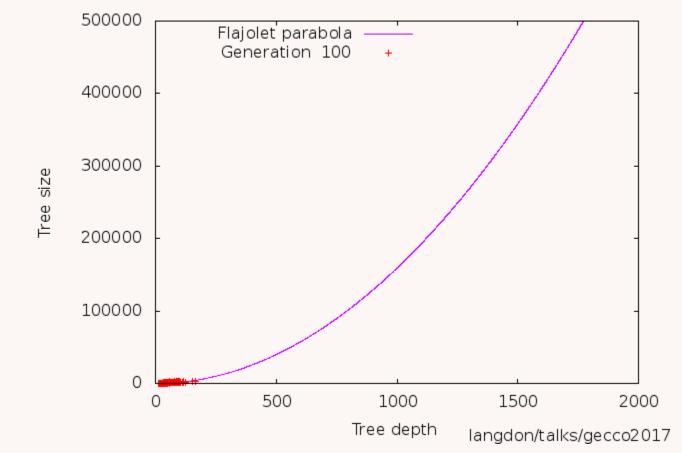
Circular lattice code <u>gp2lattice.awk</u>



Video

### Shapes of Evolved Trees

6-Mux 500 binary trees (run 100)



Both whole trees + and subtrees lie near Flajolet Depth  $\approx 2\left(\frac{\pi \ size}{2}\right)^{\frac{1}{2}}$  limit for random trees

## Bloat limited by Gambler's ruin

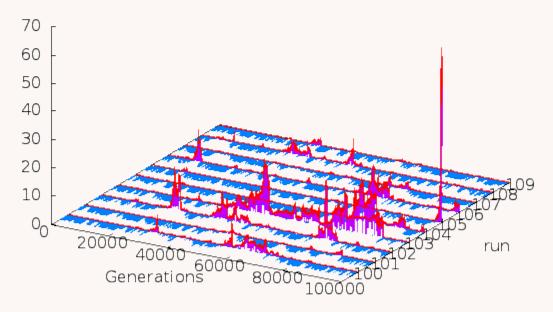
- Tiny fraction of disrupted (low fitness) children sufficient to drive evolution towards ever bigger trees.
- As trees get bigger chance of hitting protected effective code near root node falls.
- In a finite population eventually no child will be disrupted.
- Size, without fitness, wanders at random.
- But wondering towards lower limit will re-establish the conditions for bloat.

cf. Gambler's ruin.

 Very approximate limit on tree size: tree size ≈ number of trees × core code size

## Bloat limited by Gambler's ruin

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



- tree size ≈ number of trees × core code size
- tree size ≈ 50 × 497 ≈ 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/ EPSRC

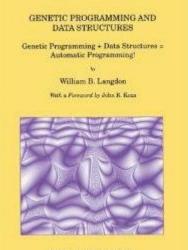
W. B. Langdon, UCL



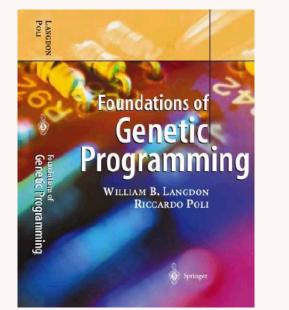
### **Genetic Programming**



### CREST Department of Computer Science



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Riccardo Poli William B. Langdon Nicholas F. McPhee

> with contributions by John R. Koza

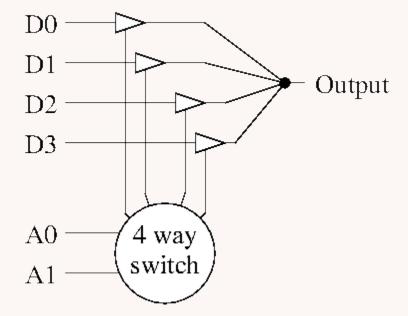


### GPquick

- 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<sup>6</sup>=64 possible combinations
- Fitness score (0-64) is number correct

## Genetic Programming to solve 6-Mux

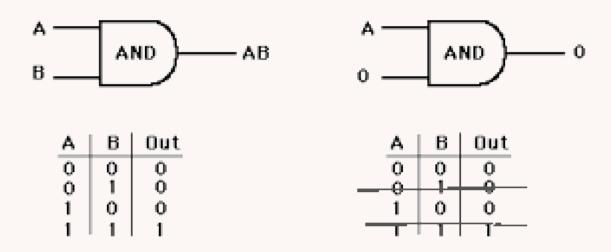
- Terminals (tree leafs)
  D0,D1,D2,D3 D4,D5
- Function set: 2 input gates → binary trees
   AND, NAND, OR, NOR. No side effects
- Generational population of 500 trees
- Tournament selection: choose best of 7
- 100% subtree crossover
- Initially hard limit on tree size (10<sup>6</sup>)



### 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.

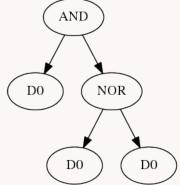
(NB no side effects)

#### CREST

### Constants

- Two constants: always 0 and always 1 (FFFFFFFFFFFFFFF).
- E.g. evolve by negating input and ANDing with same input

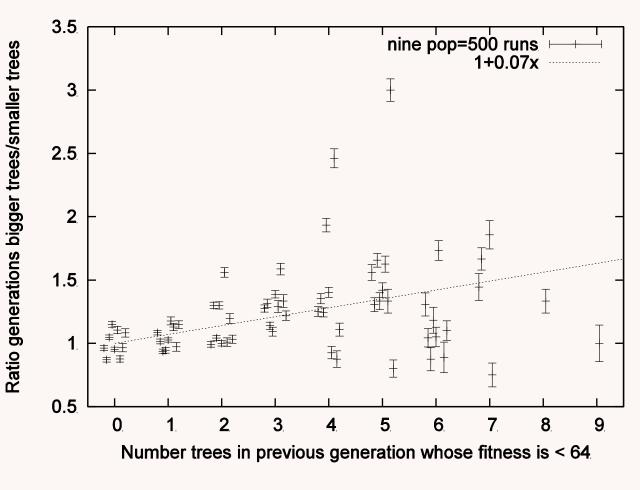
(AND D0 (NOR D0 D0)) = 0



- 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**

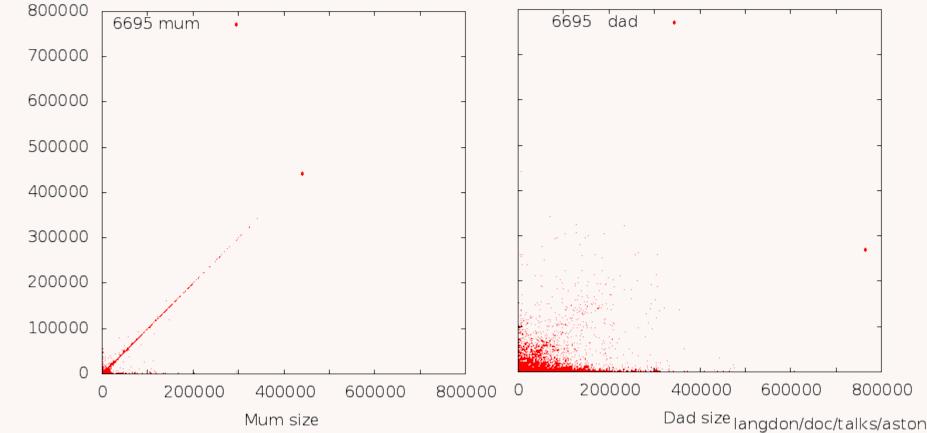


Don't plot ratio if less than 5 data



### Importance of Mothers

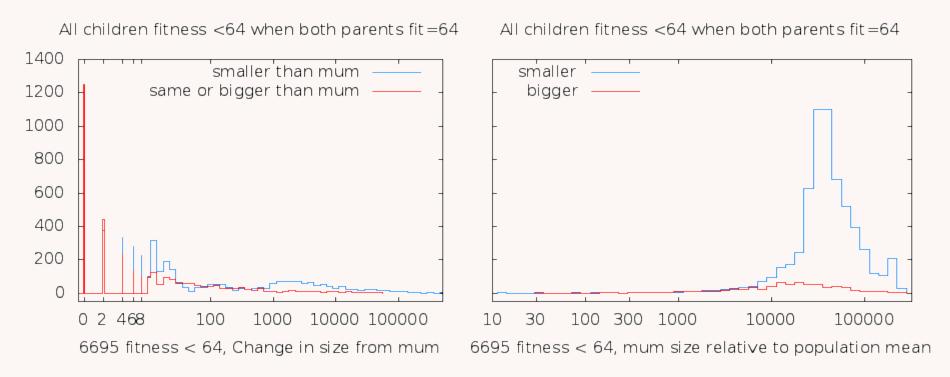
All children fitness <64 when both parents fit =64  $\,$  All children fitness <64 when both parents fit =64  $\,$ 



Size of poor fitness children closely related to parent who they inherit root from (mum).

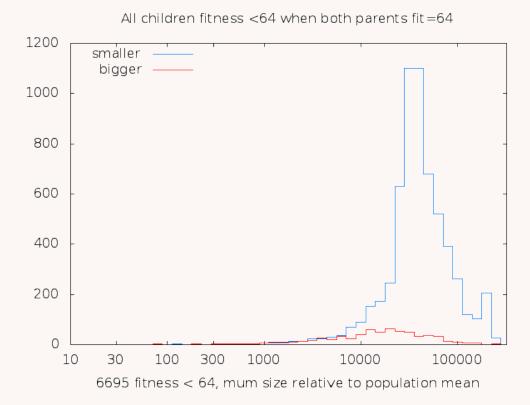


### Importance of Mothers



- 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

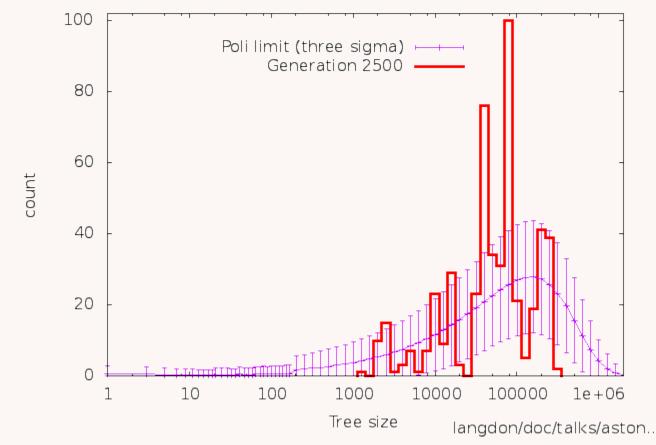
REST

Although there is noise, on average size increases



## **Testing Theory**

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

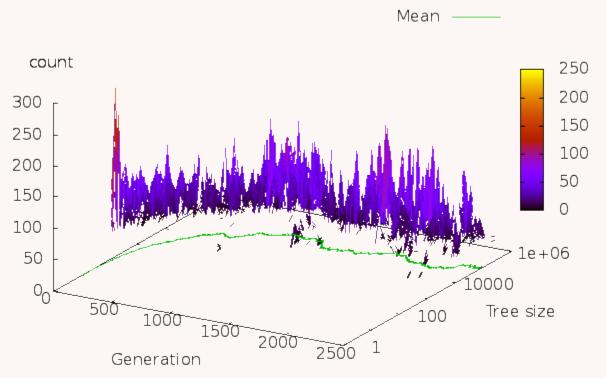


- Theory assumes crossover only (no selection). In earlier work distribution of sizes converged to limit rapidly.
- Selection caused by a few runts modifies size distribution



## **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  $\ge 3\sigma$
- 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

#### Make sure it has all of your papers!

E.g. email W.Langdon@cs.ucl.ac.uk or use | Add to It | web link

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