Naïve Crossover Biases in GP

On the Evolution of Parsimonious Solutions

Case for Parsimonious Solutions

- Avg(program size increase)
  - $\propto O(\text{generation}^2)$
- Evaluation Overhead Increases
- Solution Transparency Decreases
- Does boat $\rightarrow$ more effective search?
  - What is an effective search?
    - Does bloat $\rightarrow$ better population diversity or more duplication?
- Restrict our discussion to Tree structured GP

Generic Approaches to Date

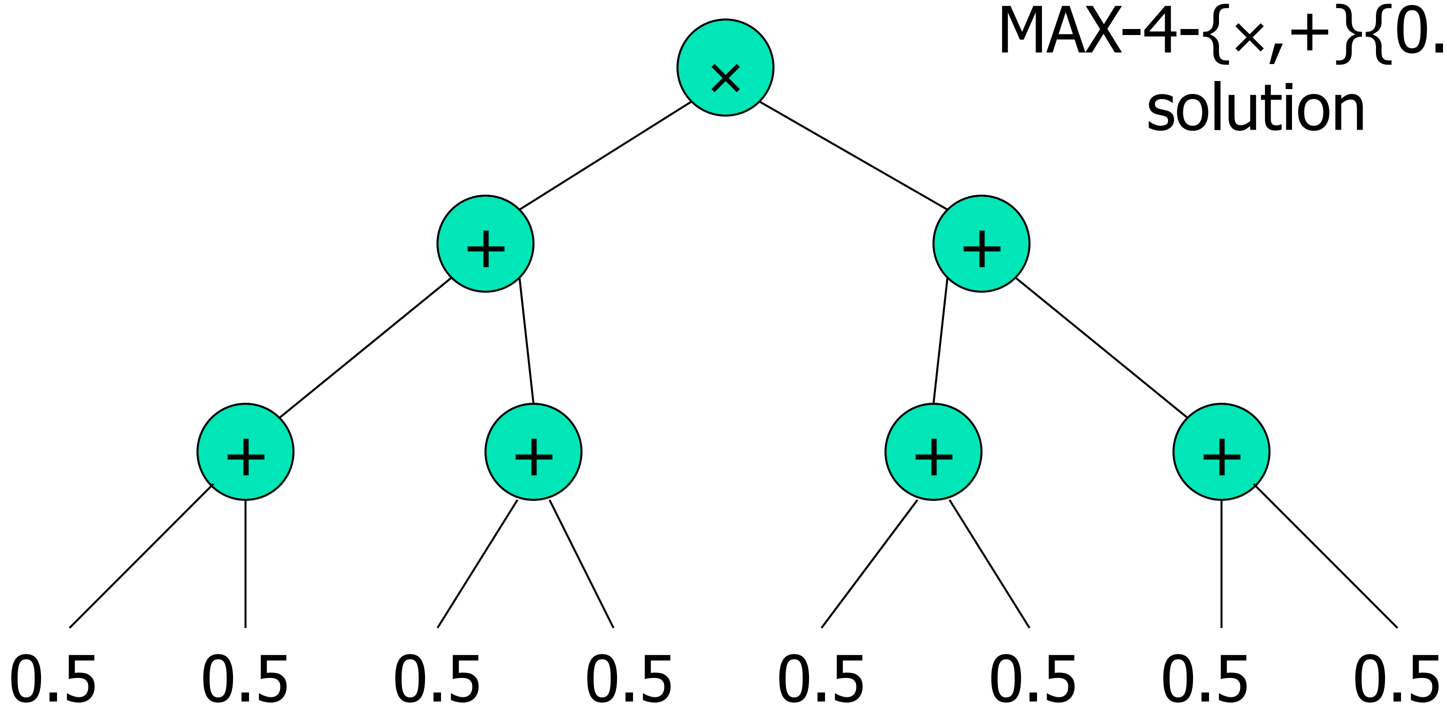
- Size and Depth Limits
  - [1]
- Parsimony Pressure
  - [2], [3], [4]
- Non-destructive crossover
  - [5]
- Biased crossover operator
  - [6], [7]

Size and Depth [1]

- Explicit,
  - Max node count/ Depth limit;
  - Unwanted interaction with crossover operator [8].

Max Problem [8]

MAX-4-{×,+}{0.5}
solution



Visualizing a tree (1)

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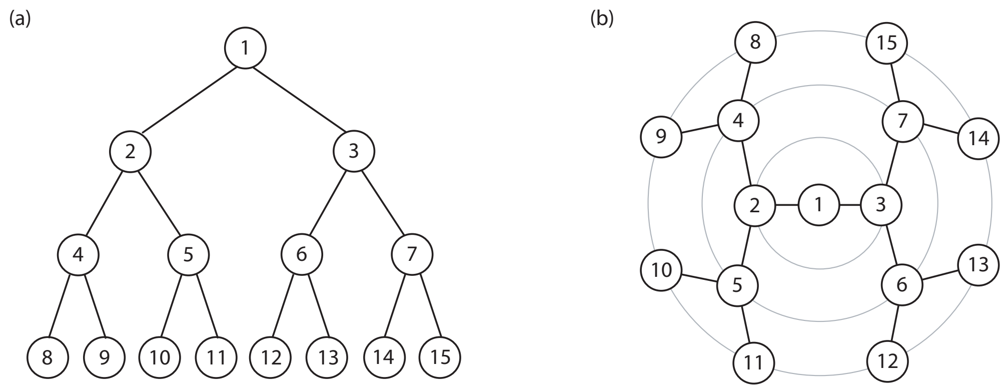

Fig. 1. Mapping a Full binary tree to a circular grid. (a) Full binary tree of depth 3. (b) Corresponding circular grid

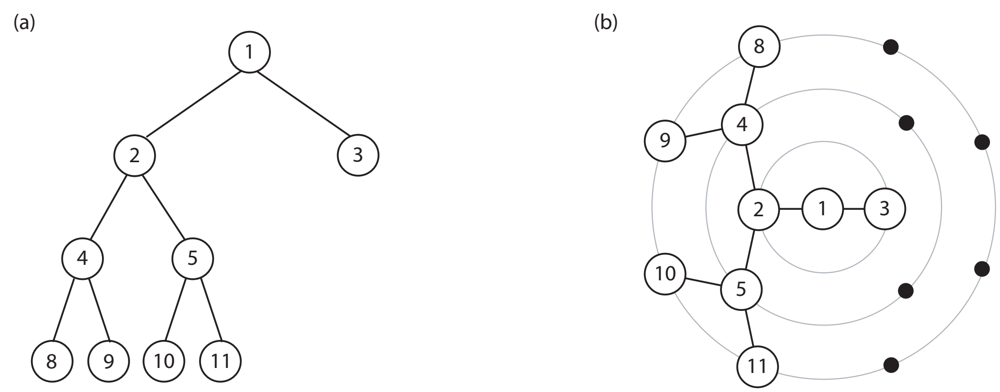

Fig. 2. Mapping an arbitrary plane binary tree to a circular grid. (a) Arbitrary plane binary tree of depth 3. (b) Corresponding circular grid

Visualizing a tree (2)

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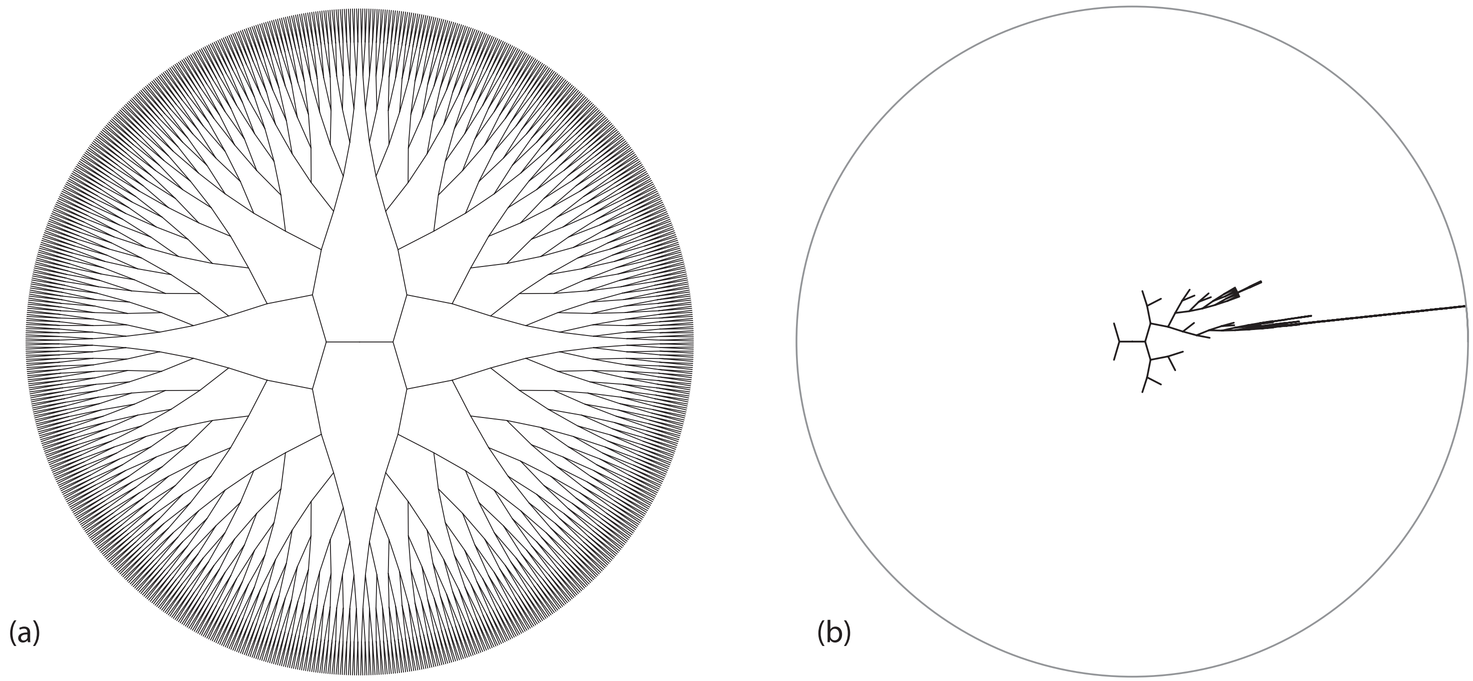

Fig. 3. Two examples of plane binary trees. (a) Full binary tree, depth 10. (b) Structure of a GP-generated solution (using arity-2 functions), depth 26. The gray circle around (b) represents depth 26 and is shown for reference

Visualizing a tree (3)
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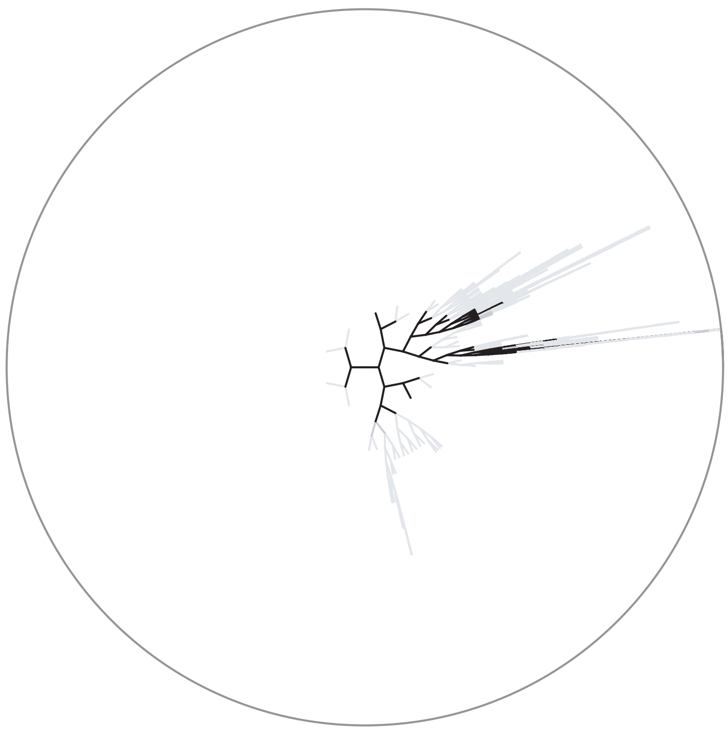
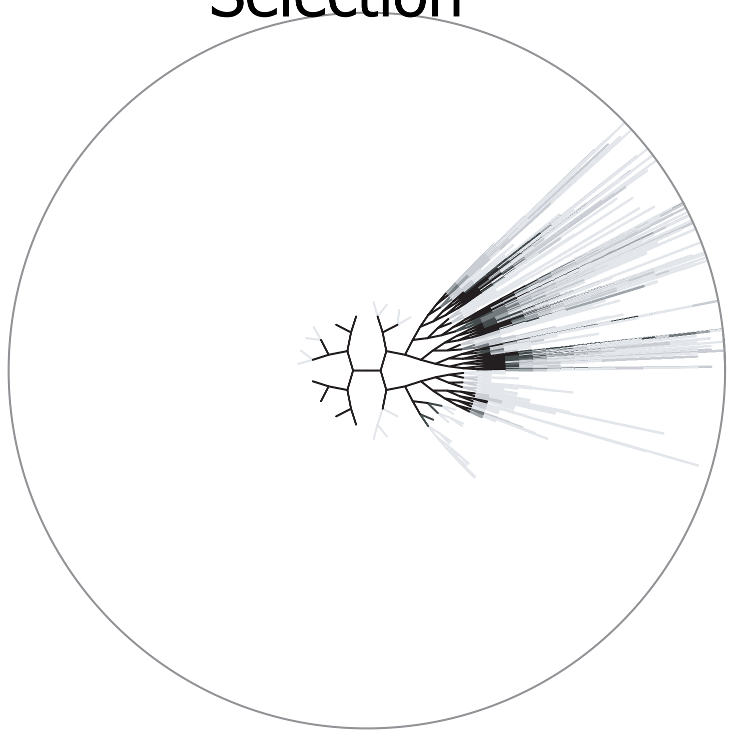
Tournament Selection



Fitness Proportional Selection



Parsimony Pressure

- Fitness = ‘error’ + α ‘complexity’ [2]
  - α is problem dependent;
  - Evolution of α ?
- Pareto Optimal [3]
  - Multi-objective fitness function
- Lexicographic [4]
  - Only use ‘complexity’ as a tie breaker;
  - Limited to countable problems?

Non-destructive Crossover [5]

- IF
  - child performance ≠ parent performance
- THEN
  - accept child
- (not to be confused with genetic 'hill-climbing')

Biased Crossover Operator

- Size Fair or Homologous Crossovers [6]
  - Emphasize routed tree approach to selection of crossover.
  - Second crossover point constrained to path defined by the first.
- Fitness direction
  - Estimate fitness with respect to each node of the individual

Fitness Direction – Motivation

- How significant are naïve biases
  - Each node has a fitness;
- Crossover only produces 1 child
  - Spend more time investigating same shape without recourse to 1-point crossover;
  - Mutation provides further investigation of reproduced ‘child’.

Selection of Crossover Point

- Random
  - Any link chosen with uniform probability.
- Deterministic
  - Select branch with respect to distance metric.
- Both
  - Provide for stochastic selection of either at some ratio.

Directed Crossover Heuristics

- Fitness
  - Estimate fitness at each node as tree evaluated
- Fitness Difference
  - Difference in node fitness
- Roulette-Fitness
  - Nodes allocated ‘roulette-wheel’ area $\propto$ node fitness

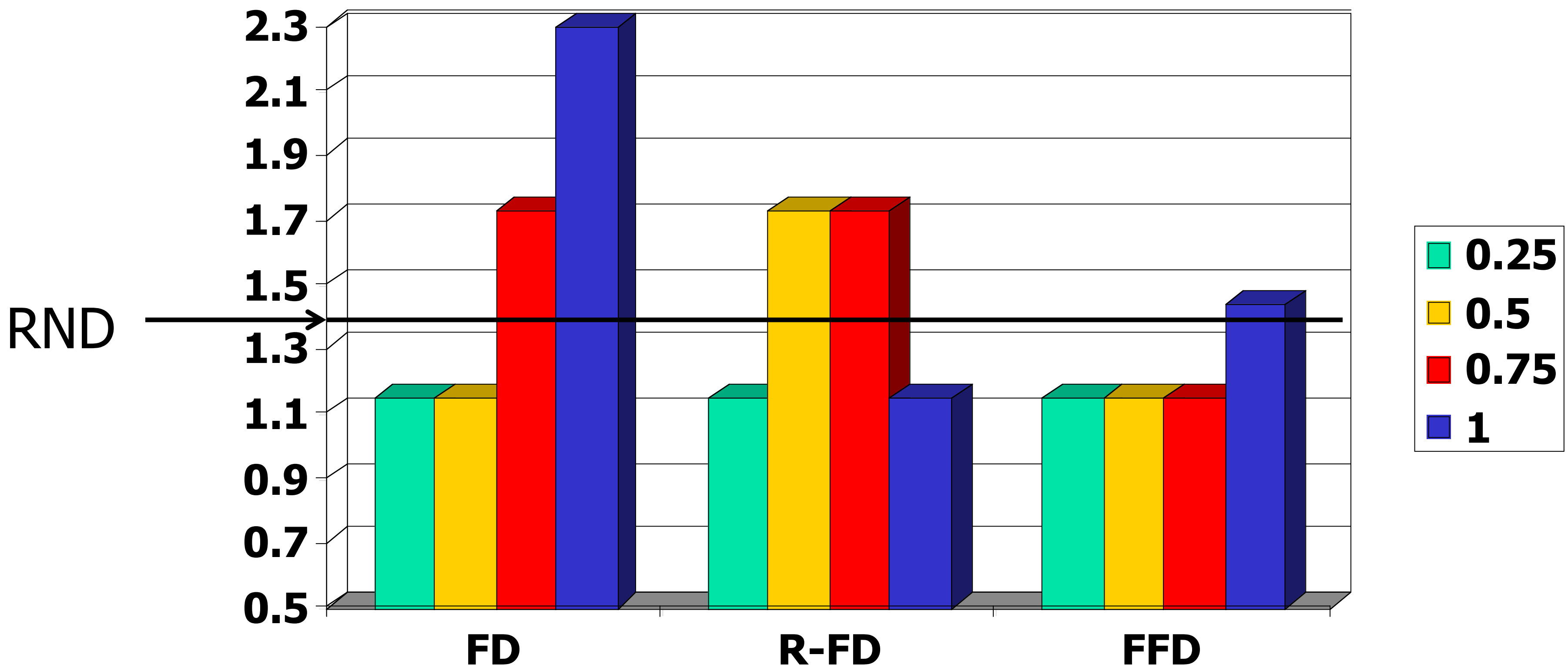
Methodology

- Investigate increasing levels of determinism
  - {0% (random only); 25%, 50%, 75% 100% (directed only)}
- Algorithm
  - IF (apply crossover == TRUE)
  - THEN IF (Directed Xover == TRUE)
    - THEN (apply Directed Xover)
    - ELSE (apply Random Xover)

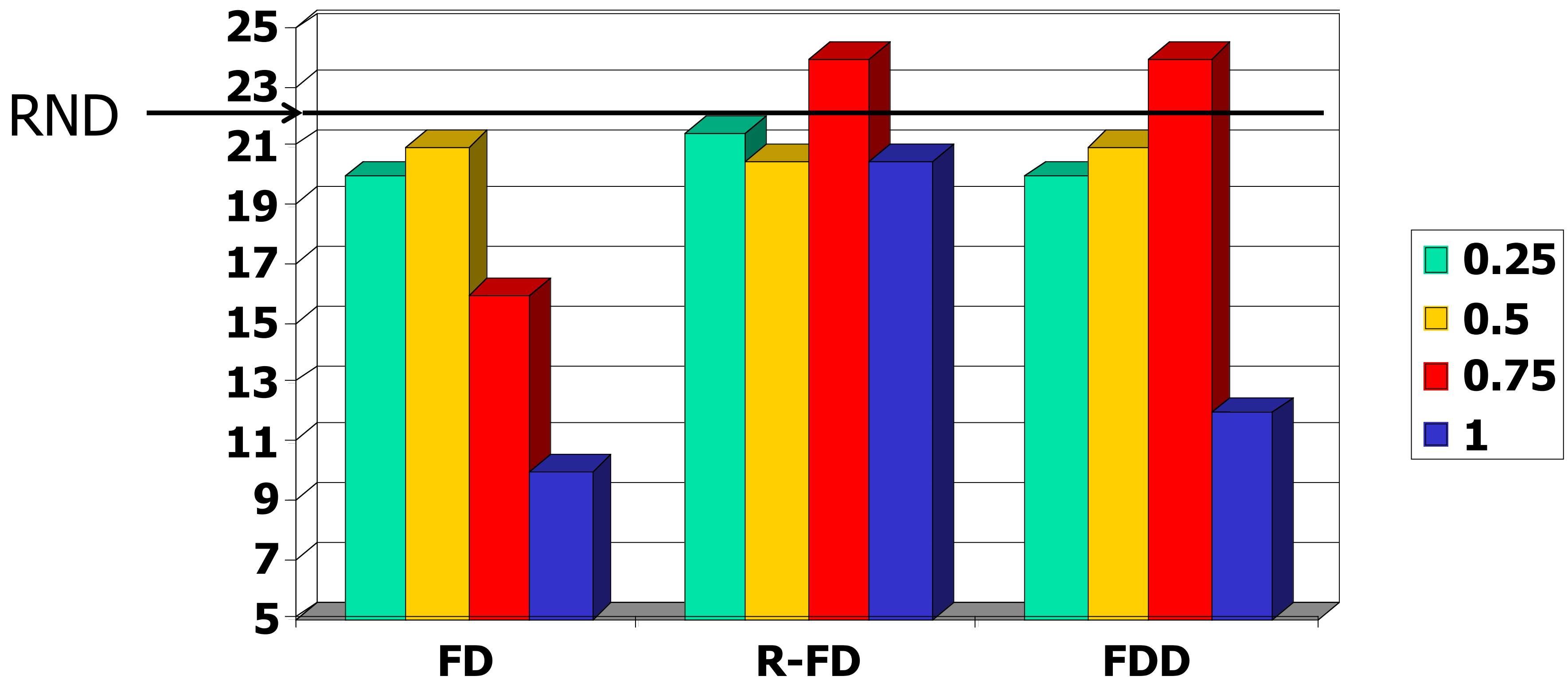
Classification Problems

Data set	Breast	Liver
Train	524	259
Test	175	86
Terminal	x(0),…,x(8)	x(0),…,x(5)
Function	+, -, *, %, sin, cos, sqrt	
Fitness	# correct classifications	
Pop. Size	500	
Search Op.	90% Xover; 50% mutation	
Termination	15,000 tournaments	

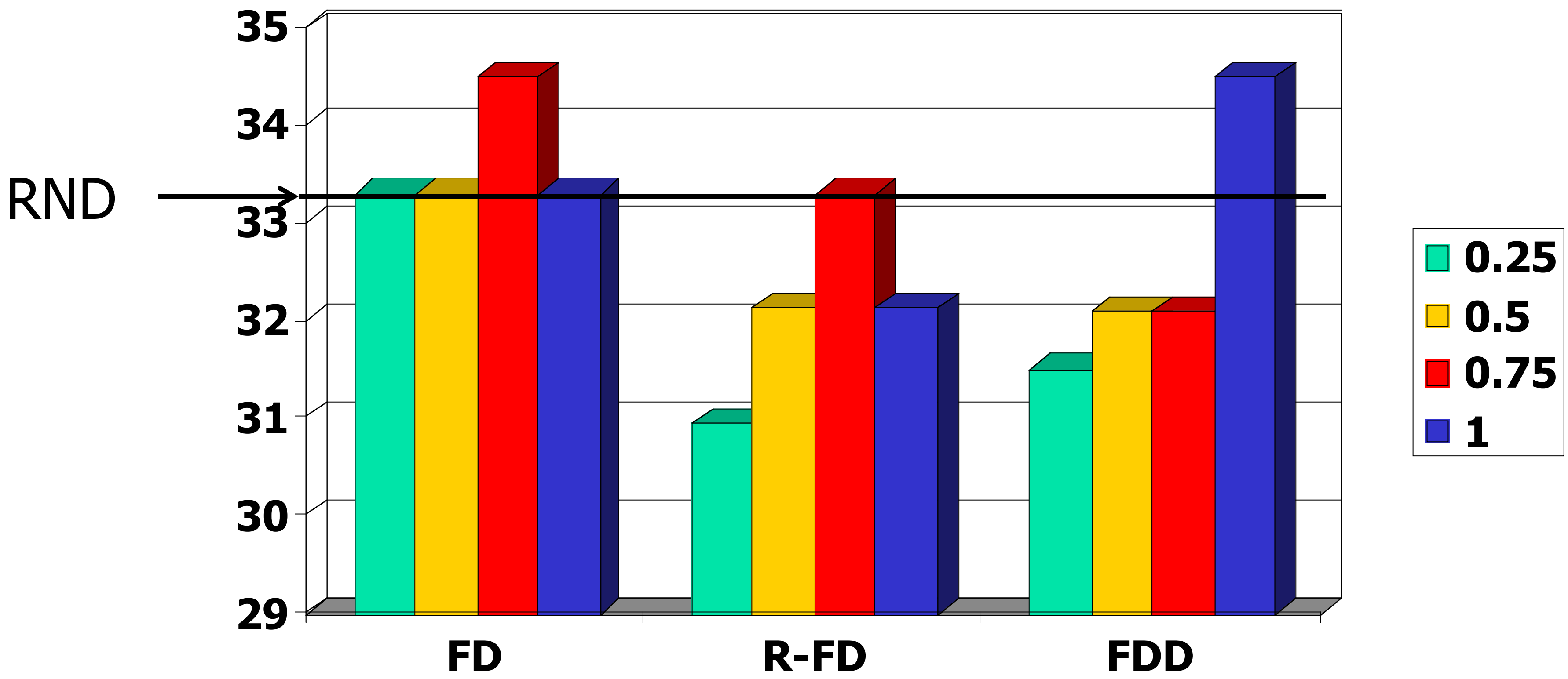
Breast Cancer – Median Test Error



Breast Cancer – Median Nodes per Solution

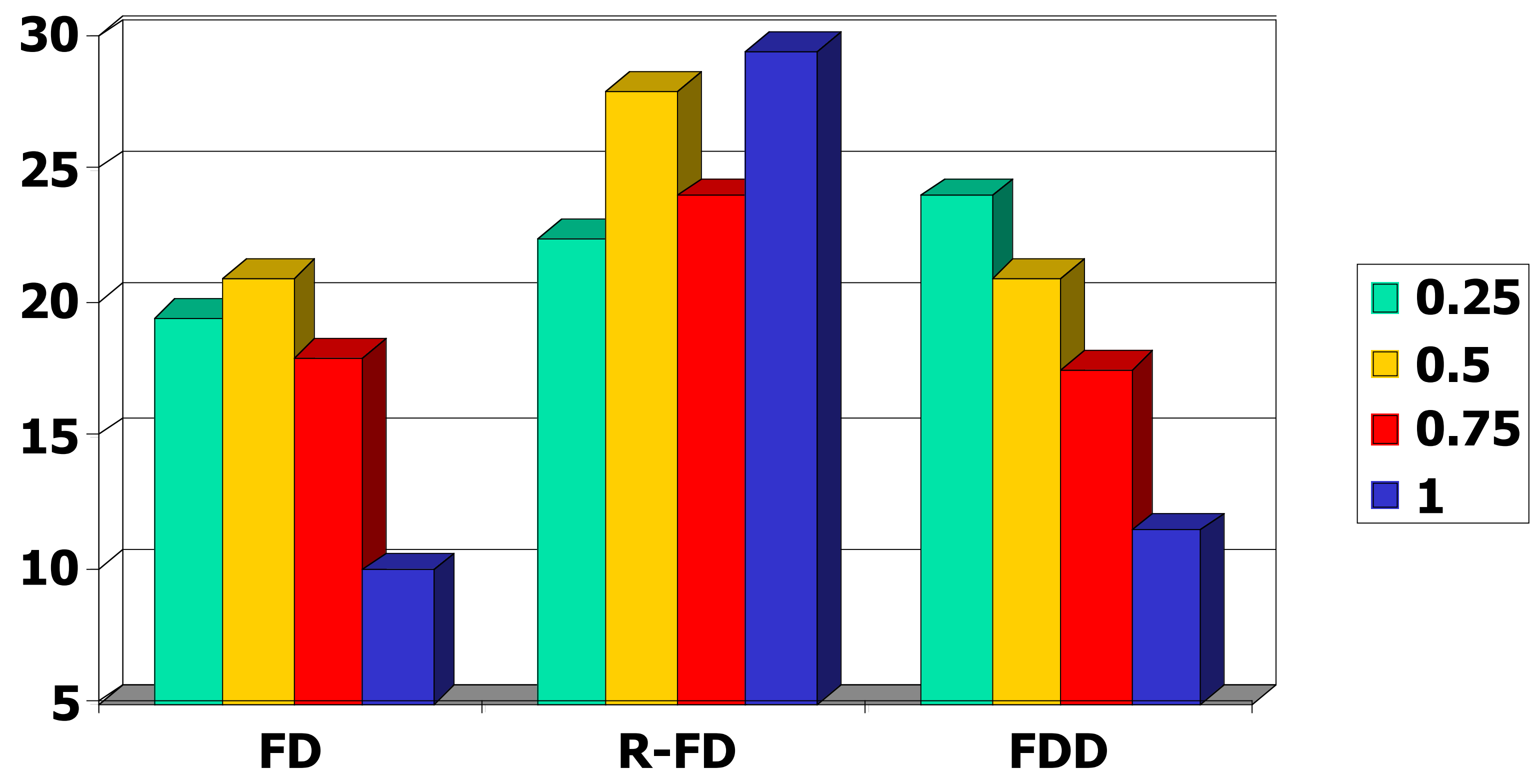


Liver Disease – Median Test Error

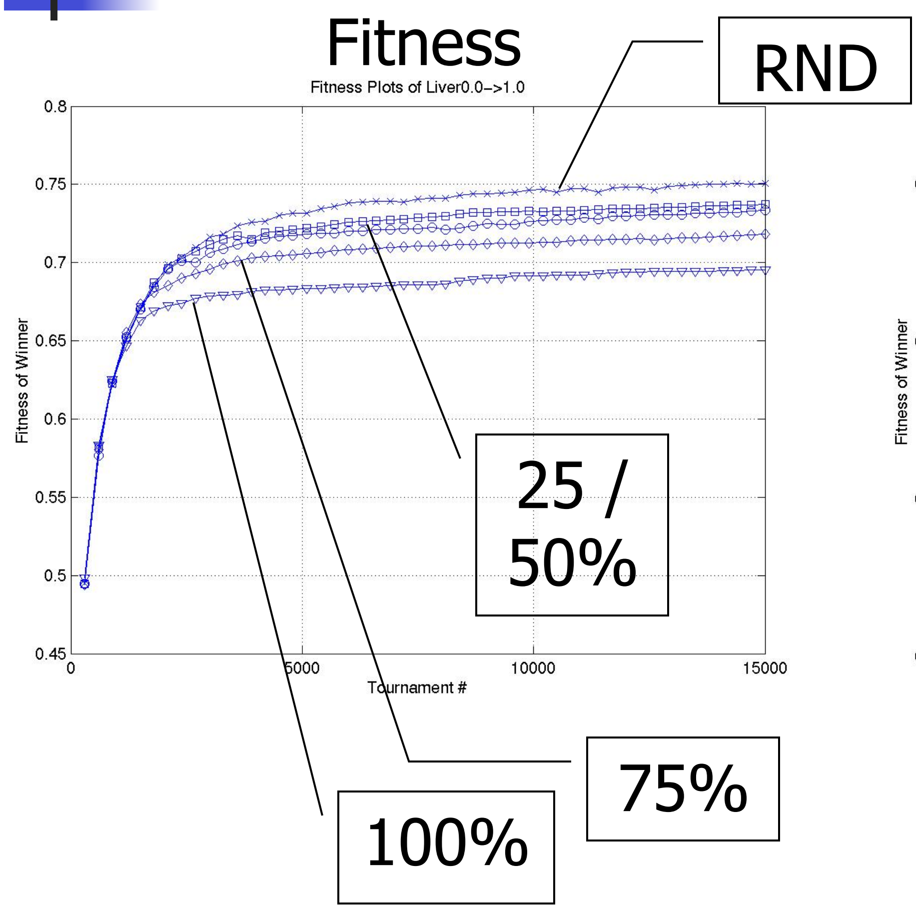


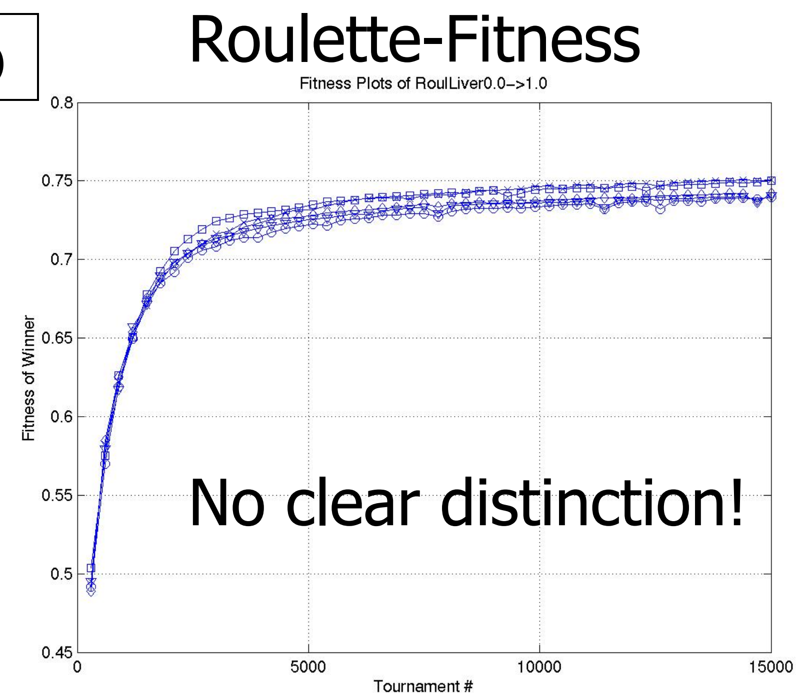
Liver Disease – Median Nodes per Solution

RND
34.5



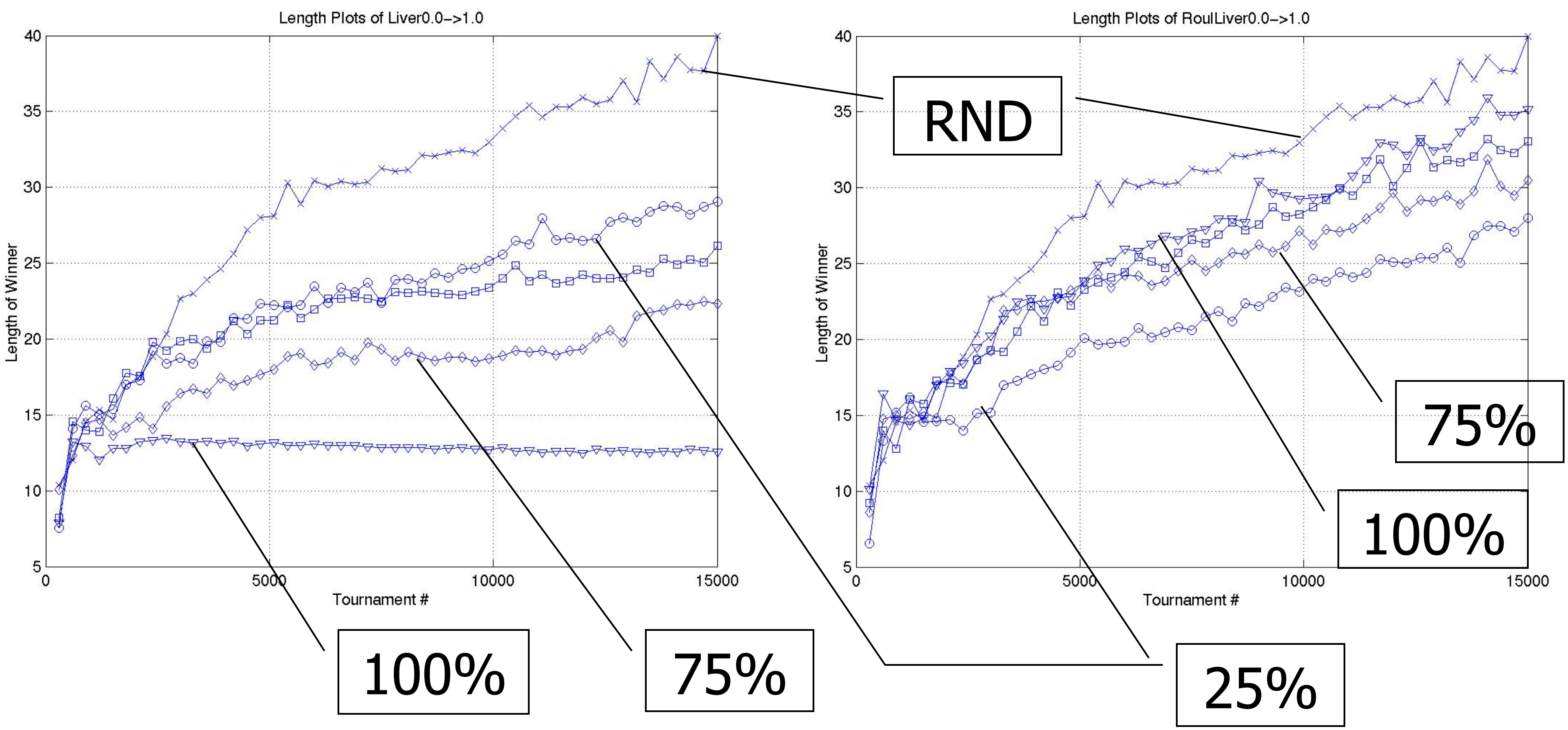
Evolution of Fitness: Liver – *Average* Classification Accuracy





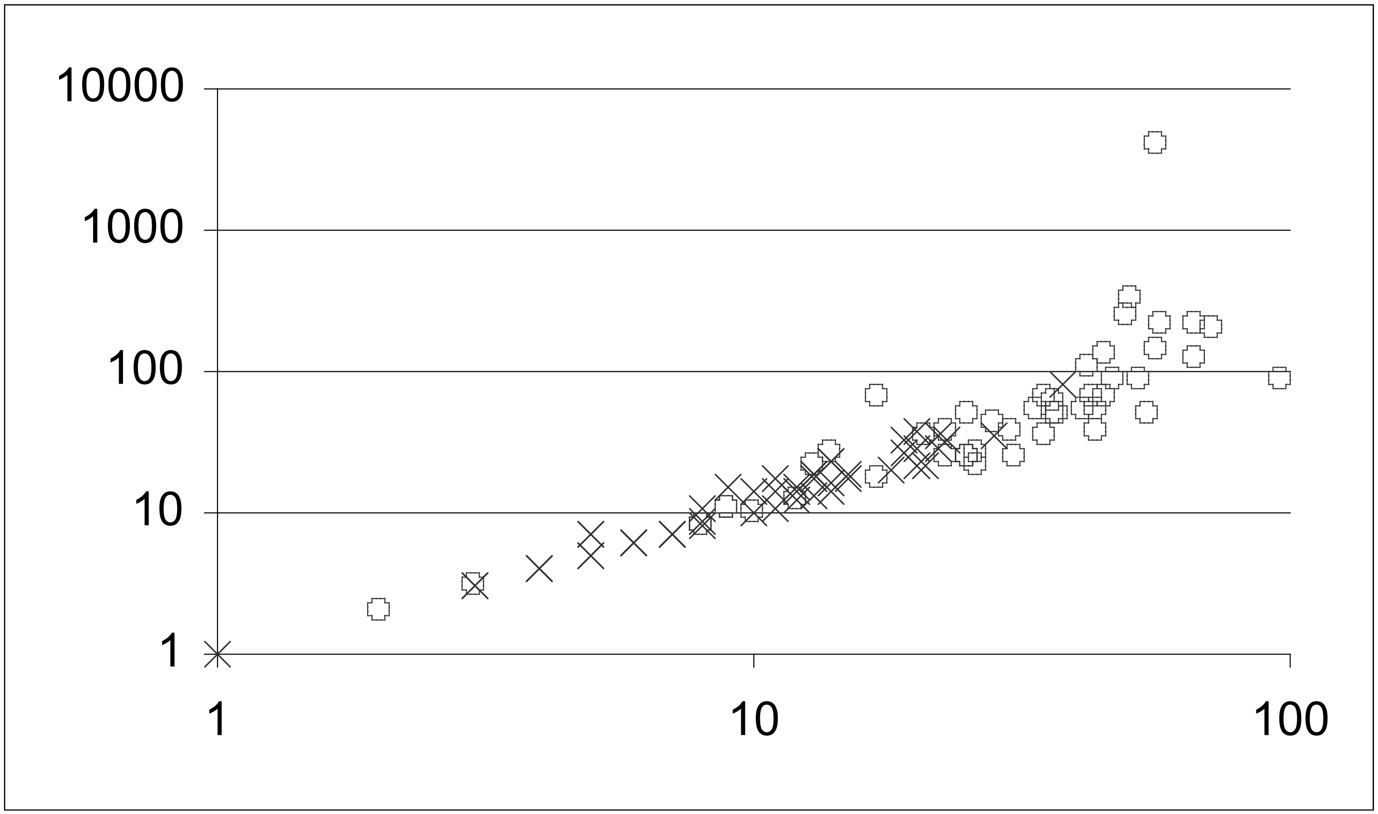
Evolution of Fitness: Liver – *Average* Node Count

Fitness | Roulette-Fitness



MAPLE™ 'simplification'

nodes After Simplification



×- FD
O - RND

nodes Before Simplification

Discussion

- Hands Off – v – Interactive
  - Removing Introns after solution located – v – Inclusion in the evolutionary cycle.
- Complexity – v – Accuracy
  - Can simple solutions still be accurate?
  - Are complex solutions useful?
- Solution bias?
  - Are biases application / difficulty specific?

References

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3. Ekart A., Nemeth S.Z., Selection based on the Pareto non-domination criterion for controlling code growth in GP. Genetic Programming and Evolvable Machines. 2(1) 61-73, 2001.
4. Luke S., Panait L., Lexicographic Parsimony Pressure. GECCO' 2002. Morgan Kaufmann, 829-836.

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5. Soule T. Foster J.A., Removal Bias, Proceedings of IEEE Int. Congress on Evolutionary Computation. 781-786, 1998.
6. Langdon W.B., Size Fair and Homologous Tree Crossovers for Tree GP. Genetic Programming and Evolvable Machines. 1(1/2) 95-120, 2000.
7. Terrio D., Heywood M.I., On Naïve Crossover Biases with Reproduction for Simple Solutions to Classification Problems. GECCO, 2004.
8. Gathercole C., Ross P., An adverse interaction between crossover operator and a restriction on tree depth. Proceedings of the First Annual Conference on GP. 291-296, 1996.
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