#### Repeated Sequences in Genetic Programming

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# Introduction

- Langdon + Banzhaf in Memorial University, Canada
- Emergence: Repeated Sequences
- Repeated Sequences in Biology
- Linear and Tree Genetic Programming
- Test problems
- Repeated sequences, fragments and subtrees
- Movies
- So what?
  - Where does this lead next?
  - Other emergent phenomena?
- Conclusions

# Emergence

- Emergence of effects that have not been explicitly programmed into the system.
- Simple rules lead to complex behaviour. Intelligence emerging from many trivial interactions.
- Particle Swarm Optimisation (PSO)
  - Flocking
  - Boids



- Swarm intelligence
- Genetic Programming
  - Bloat
  - Repeated Sequences

# Repeats in DNA

- Many different types of repeated DNA sequence. Classified by repeat sequence length, number of repeats, location in DNA molecule etc. etc.
  - Some may have biological meaning, e.g. as a clock counting cell divisions and enforcing limit, cell life limited, so cancer prevented.
  - Repeated sequences in both expressed (protein coding) and non-expressed DNA.
- DNA whose sequence is not maintained by selection will develop periodicities as a result of random crossover [G.P. Smith, 1976].

# **Demonstration problems**

- Want to run GP for many generations. Hard problems, not immediately solved.
- Want range of different problems
  - Time series modeling. One variable, short integers (byte) arithmetic
  - Bioinformatics. Binary classification, floating point, 20 inputs.

#### Mackey-Glass Chaotic Time Series

- Hard (impossible) since chaotic time series.
- IEEE benchmark, 1201 data points.
- Fast signal processing (integer arithmetic)
- 7 time lags: 1, 2, 4, ..., 128 steps ago.

#### Mackey-Glass



Mackey Glass benchmark and first Evolved (2XO) Function

# **Predicting Protein Location**

- Given only number of each amino acid (i.e. cheap info, Swissprot) in a protein, predict what it is. Very hard.
- Easier: predict where the protein will be found
  - Simplified (A. Reinhardt and T. Hubbard, 1998) which covers animals and microbes, to just animals and two classes: In the cell nucleus or not.

#### **Animal Nuclear Proteins**

Nuclear and Non-Nuclear Animal Protiens



Non-linear 2D projection from 20 Dimensional Space

#### **Animal Nuclear Proteins**



Non-linear 2D projection from 20 Dimensional Space

#### Genetic Programming Approaches

- Linear GPengine (Nordin)
  - crossover with mutation
  - Headless chicken mutation (HCX) only
- Linear Machine Code Discipulus
- Tree GP

# Linear Genetic Programming

- Chromosome is program.
  - A linear sequence instructions
  - Executed from start to end (no loops)
- GPengine interpreted.

#### Discipulus Intel 486 instructions

# Linear GP Chromosome

- GPengine instruction format
- 90% Crossover

OutputArg 1OpcodR0R7R0R7+ - *	le Arg 2 / 0r R0R7
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- 40% Mutation. Pop 500.
- Two point (4 crossover chosen independently)
- Homologous (parent crossover points aligned)



#### **Performance** (all approaches solve problems) **Predicting M-G chaotic Time Series RMS** error Mean 1.6-5.4 Linear GP 3.8 1.1 - 4.9Tree GP 3.5 **Nuclear Protein prediction (holdout set)** Discipulus 78-82% 80% 78-83% 81% Tree GP

#### **Evolution of Mackey-Glass error**



Mackey-Glass GPengine Evolution of population fitness distribution

#### Evolution of M-G program length



Mackey-Glass GPengine Evolution of population Lengths

#### Length of Repeated Sequences



#### Longest Repeats M-G and Protein



Longest repeated sequence in Mackey-Glass and Protein Location best of run programs



- Red arrow indicates length of program.
- Single repeated instructions are not shown.
- Repeated pairs of instructions are shown in red.
- Repeated sequence of 3 instructions in blue.
- Four or more are plotted with purple lines.
- Length and Fitness, RMS error, as numbers. <sup>19</sup>

# **Evolution of Location of Repeated Instructions**

- First two point crossover Mackey-Glass
  GPengine run
  - <u>http://www.cs.ucl.ac.uk/staff/W.Langdon/gecc</u> <u>o2004lb/int6.0.all.rep2\_movie.gif</u>



- Dot at i,j means instruction at location i is identical to that at location j.
- 1-10 repeated instructions are shown with red.
- 11 or more repeated sequence shown in blue.
- Length and Fitness, RMS error, given numerically.
- Same Mackey-Glass 2point crossover run

# Animation

- 250 generations Mackey-Glass GPengine
  - <u>http://www.cs.ucl.ac.uk/staff/W.Langdon/gecc</u> <u>o2004lb/int6.0.250.movie.gif</u>

### Effective Code

- Majority of instructions have no effect on the output of the programs.
- No obvious link between repeat and effectiveness

# Introns and Repeats evolved in one Mackey-Glass program



Effective code in best of 1st 2XO Mackey-Glass run

# Information Content

 Lempel-Ziv compression shows bloated programs' contain less information than random program of same length.

#### **Evolution of Information Content**



Evolution of Information and Length of best in population 1st 2XO Mackey-Glass run

#### Repeats in largest Protein Prediction program



#### **Important Nodes**



#### Black changes >10 training cases

# Discussion

- In trees, can get *diffuse introns* whereby whole program depends only on fraction of tree. Not classic introns, since most functions do depend on both arguments.
- Crossover evolves trees similar fractal shape properties as random trees BUT
- Repeats not random.
- Many subtrees have high fitness and pass information towards root, BUT
- Much of program can be discarded with little impact on fitness
- Genetic programming on simple problems assembles complete solutions by gradually, randomly, reusing existing partial solutions to get small improvements, rendering existing parts less important.

# Conclusions

- On different problems and different GPs (2 linear and tree) where length is not constrained, repeated sequences/subtrees/fragments emerge from crossover
- Repeats cover large fraction of fit programs.
- This is an example of *emergence*.
  - Are there examples in your EA of effects (which were not pre-programmed) which spontaneously evolved?

# More information

References:

Repeated Sequences in Linear GP Genomes, W.B. Langdon and W. Banzhaf, <u>(GECCO'2004</u> late breaking paper <u>PDF gzipped postscript)</u>. <u>Movie. Poster</u>

Smith, G.P. (1976) "Evolution of Repeated DNA Sequences by Unequal Crossover." *Science*, 191(4227), 528-535. [PDF]).

#### More information on GP

- <u>http://www.cs.ucl.ac.uk/staff/W.Langdon/</u>
  - Foundations of GP, Springer, 2002
  - GP and Data Structures, Kluwer, 1998
- <u>http://liinwww.ira.uka.de/bibliography/Ai/genetic.prog</u> <u>ramming.html</u>
- http://www.cs.ucl.ac.uk/staff/W.Langdon/lisp2dot.html

# **GPengine Mackey-Glass**

Objective:	Evolve a prediction for a chaotic time series
Function set:	$+ - \times \div^{a}$ (operating on unsigned bytes)
Terminal set:	8 read-write registers, constants 0127. Registers
	are initialised with historical values of time series.
	R0 128 time steps ago, R1 64, R2 32, R3 16, R4 8,
	R5 4, R6 2 and finally R7 with the previous value.
	Time points before the start of the series are set to
	zero.
Fitness:	Root mean error between GP prediction (final value
	in R0) and actual (averaged over 1201 time points).
Selection:	Steady state, tournament 2 by 2
Initial pop:	Random program's length uniform chosen from 114
Parameters:	Population 500, max program size 500,
	90% crossover, 40% mutation
Termination:	125 500 individuals evaluated

<sup>*a*</sup>If second argument of  $\div$  is zero,  $\div$  returns zero.

Table 1. GPengine parameters for Mackey-Glass time series prediction.

### **Discipulus Protein Prediction**

Objective:	Evolve a prediction of nuclear or non-nuclear loca-
	tion for animal proteins based on their amino acid
	composition
Terminal set:	2 read-write FPU registers, 43 randomly chosen con-
	stants. Number (integer) of each of the 20 amino
	acids in the protein. (Codes B and Z are ambigu-
	ous. Counts for B were split evenly between aspartic
	acid D and asparagine N. Those for Z between glu-
	tamic acid E and glutamine Q.)
Fitness:	DSS [39, 37]. Parsimony not used.
Selection:	Steady state, tournament 2 by 2
Initial pop:	Random program's length uniform chosen from
	480 bytes
Parameters:	Population 500 ( $10 \times 50$ demes), max program size
	2048 (bytes), 95% crossover (either all 2XO or
	95% HCX and 5% 2XO) 95% mutation (three types
	30%, 30%, 40%)
Termination:	500 000 individuals evaluated

Table 3. Discipulus parameters used in animal protein location prediction experiments. Only the maxiumnum program size and HCX were changed from factory defaults.

#### Tree Mackey-Glass (Protein Localisation)

Function set: MUL ADD DIV SUB operating on unsigned bytes (proteins: floats) Terminal set: Registers are initialized with historical values of time series. D128 128 time steps ago, D64 64, D32 32, D16 16, D8 8, D4 4, D2 2 and finally D1 with the previous value. Time points before the start of the series are set to zero. Constants 0..127. Proteins: Number (integer) of each of the 20 amino acids in the protein. (Codes B and Z are ambiguous. Counts for B were split evenly between aspartic acid D and asparagine N. Those for Z between glutamic acid E and glutamine Q.) 100 unique constants randomly chosen from tangent distribution (50% between -10.0 and 10.0) [8]. (By chance none are integers.) RMS error Fitness:  $\frac{1}{2}$ True Positive rate  $+\frac{1}{2}$ True Negative rate [9] Selection: generational (non elitist), tournament size 7. Pop Size 500 (5000). Tree created by ramped half-and-half (2:6)  $(\frac{1}{2} \text{ terminals are constants})$ Initial pop: Parameters: 50% mutation (point 22.5%, constants 22.5%, shrink 2.5% subtree 2.5%). Maximum tree size 1000. Either 50% subtree crossover or 50% size fair crossover, (90% must be on internal nodes) crossover fragments  $\leq 30$  [7] Termination: 50 generations