Massachusetts Institute of Technology

Genetic Programming

A Tutorial Introduction

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Instructor: Una-May O'Reilly

- Leader: AnyScale Learning For All Group, MIT CSAIL
- Experience solving real world, complex problems requiring **machine learning** where **large scale evolutionary computation** is a core capability
- Applications include
  - ICU clinical data mining
  - Behavioral data mining – MOOC
  - Circuits, network coding
  - Sparse matrix data mapping on parallel architectures
  - Finance
  - Flavor design
  - Wind energy
    - » Turbine layout
    - » Resource assessment
- Focus on innovation in genetic programming
  - Improving its competence

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Tutorial Goals

- Introduction to GP algorithm, given some knowledge of genetic algorithms or evolutionary strategies
  - Enable Black box demonstration of GP symbolic regression
- Become familiar with GP design properties and recognize them
- You could teach it in an undergrad lecture
- Try it "out of the box" - with software libraries of others
- Set groundwork for advanced topics
  - Theory
  - Specialized workshops – Symbolic Regression, bloat, etc
  - GP Track talks at GECCO, Proceedings of EuroGP, Genetic Programming and Evolvable Machines

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Agenda

Context: Evolutionary Computation and Evolutionary Algorithms

1. GP is the genetic evolution of <u>executable</u> expressions
   - Black box example of GP symbolic regression
2. Nuts and Bolts Descriptions of Algorithm Components
3. Resources and reference material
4. Examples
5. Deeper discussion (time permitting)

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Agenda

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Neo-Darwinian Evolution

- Survival and thriving in the environment
- Offspring quantity - based on survival of the fittest
- Offspring variation: genetic crossover and mutation
- Population-based adaptation over generations

Agenda

Context: Evolutionary Computation and Evolutionary Algorithms
- Problem domains

Problem Domains where EAs are Used

- Where there is need for complex solutions
  - evolution is a process that gives rise to complexity
  - a continually evolving, adapting process, potentially with changing environment from which emerges modularity, hierarchy, complex behavior and complex system relationships
- Combinatorial optimization
  - NP-complete and/or poorly scaling solutions via LP or convex optimization
  - unyielding to approximations (SQP, GEO-P)
  - eg. TSP, graph coloring, bin-packing, flows
  - for: logistics, planning, scheduling, networks, bio gene knockouts
  - Typified by discrete variables
  - Solved by Genetic Algorithm (GA)

Problem Domains where EAs are Used

- Continuous Optimization
  - non-differentiable, discontinuous, multi-modal, large scale objective functions
  - applications: engineering, mechanical, material, physics
  - Typified by continuous variables
  - Solved by Evolutionary Strategy (ES)
- Program Search
  - system identification aka symbolic regression, modeling
  - Symbolic regression is a form of supervised machine learning
    - » GP offers some unsupervised ML techniques as well
      - Clustering
  - Perfect seque to a blackbox GP example
    - » From
      - http://flexgp.github.io/gp-learners/sr.html
      - http://flexgp.github.io/gp-learners/blog.html

Blackbox Example of GP Symbolic Regression

http://flexgp.github.io/gp-learners/sr.html
http://flexgp.github.io/gp-learners/blog.html

S/W by ALFA Group's FlexGP team
Special recognition to Ignacio Arnaldo, PhD who prepared SR Learner tutorial and blog post

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Regression

Inputs					Output
$x1^4$	$x1^3$	$x1^2$	$x1^1$	>	
$x2^4$	$x2^3$	$x2^2$	$x2^1$	> System f(X)	> y^4 y^3 y^2 y^1
$x3^4$	$x3^3$	$x3^2$	$x3^1$	>	

AKA
Explanatory variables
Independent variables
Manipulated variables
Control variables
features

Response variable
Dependent variable
label

GOAL: FIND F(X) THAT GENERATES Y

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Regression

- Regress a relationship between a set of explanatory variables and a response variable
- Linear regression:
  - Assume linear model: y=ax+b
  - Optimize parameters (a,b) so data best fits model
- Logistic regression for classification
  - Maps linear model into sigmoid family

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$

- Symbolic regression does NOT assume a model
  - Not parameter search
  - Model is intrinsic in GP solutions

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FlexGP's SR Learner

- Targeted partly to be black-box for non-researchers
- sr.jar is available for download
  - Only supported for Debian linux
  - Source is on
    - http://flexgp.github.io
- functionality both for performing Symbolic regression on numerical datasets and for testing the retrieved models
- Referred to as our baseline in time-aligned ALFA group publications
  - Bring Your Own Learner! A cloud-based, data-parallel commons for machine learning, Ignacio Arnaldo, Kalyan Veeramachaneni, Andrew Song, Una-May O'Reilly. IEEE Computational Intelligence Magazine. Special Issue on Computational Intelligence for Cloud Computing (Feb. 2015), Vol 10, Issue 1, pp 20-32.
  - Multiple regression genetic programming, Ignacio Arnaldo, Krzysztof Krawiec, Una-May O'Reilly, GECCO '14, pp 879--886.
- Option to accelerate runs with C++ optimized execution
  - Requires gcc and g++ compilers, configuring Linux kernel parameter governing the maximum size of shared memory segments
- Option to accelerate runs with CUDA (GPU)
  - Added requirement of nvcc compiler
  - append the *-cuda* flag, make some extra directories…
- Easy parameter changing through a central file

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EA Generation Loop

Each generation

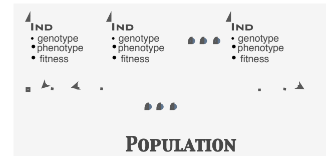
- **select**
- **breed**
- **replace**

```
population = random_pop_init()
generation = 0
while needToStop == false
    generation++
    phenotypes =decoder(genotypes)
    calculateFitness(phenotypes)
    parents = select (phenotypes)
    offspring = breed(parents.genotypes)
    population = replace(parents, offspring)
    solution = bestOf(population)
    recheck(needToStop)
```

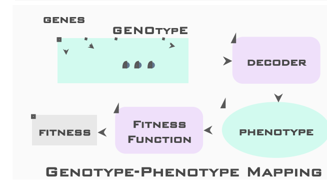

Key EA Data Structures

POPULATION

- **array of struct ind with fields genome, phenotype fitness**
- **random initialization**



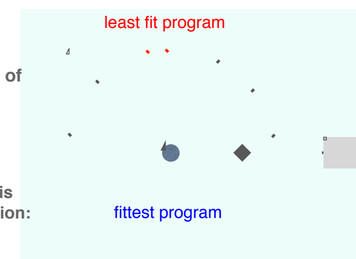
- **GENOTYPE is an set of gene(s)**
- **GENOTYPE is input parameter to decoder procedure that returns PHENOTYPE**
- **PHENOTYPE is input parameter to fitness-evaluation routine that returns a numeric variable called FITNESS**



EA Selection

Principles:

- **everyone has non-zero probability of being an ancestor**
- **individual fitness relative to population mean fitness or rank of fitness is important**
- **Sometimes the best of a population is always bred directly into next generation: "elitism"**

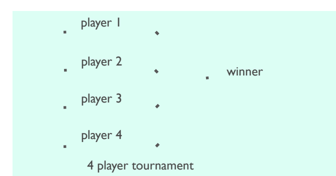


Some standard methods:

- **Roulette wheel**
- **Tournament Selection**
  - **n tournments of size k**

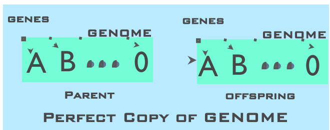
***We give the algorithm a "seed" for its RNG.**

EA Tournament Selection

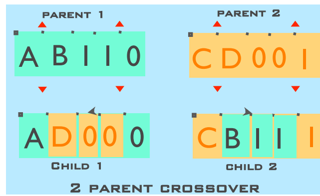


EA Breeding

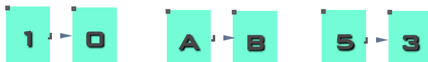
- Replication of parent [inheritance]



- crossover - [sexual recombination]



- mutation - [imperfect copy]



Choose crossover points and apply mutation randomly
Use a random number generator

EA Replacement

Deterministic

- use best of parents and offspring to replace parents
- replace parents with offspring

Stochastic

- some sort of tournament or fitness proportional choice
- run a tournament with old pop and offspring
- run a tournament with parents and offspring

EA Pseudocode

```
population.genotypes = random_pop_init()
population.phenotypes =decoder(population.genotypes)          birth
population.fitness= calculate_fitness(population.phenotypes)  development
                                                              fitness for breeding
generation = 0
while needToStop == false                                     generations
    generation++
    parents.genotypes = select (population.fitness)           select
    offspring.genotypes = crossover_mutation(parents.genotypes)   breed
    offspring.phenotypes =decoder(offspring.genotypes)        development
    offspring.fitness= calculate_fitness(offspring.phenotypes)    fitness for breeding
    population = replace(parents.fitness, offspring.fitness)  replace
    refresh(needToStop)

solution = bestOf(population)
```


EA Individual Examples

Problem	Gene	Genome	Phenotype	Fitness Function
TSP	110	sequence of cities	tour	tour length
Function optimization	3.21	variables x_of function	f(x)	|min-f(x)|
graph k-coloring	permutation element	sequence for greedy coloring	coloring	# of uncolored nodes
investment strategy	rule	agent rule set	trading strategy	portfolio change
Regress data	Executable sub-expression	Executable expression	model	Model error on training set (L1, L2)

Agenda

Context: Evolutionary Computation and Evolutionary Algorithms

1. GP is the genetic evolution of executable expressions

Koza's Executable Expressions

Pioneered circa 1988

- Lisp S-Expressions
  - Composed of primitives called 'functions' and 'terminals'

Example:

- primitives: + - * div a b c d 4
- (*(- (+ 4 c) b) (div d a))

In a Lisp interpreter:

1. bind a b c and d
2. Evaluate expressions

```
% Lisp interpreter
(set! a 2) -> 2
(set! b 4) -> 4
(set! c 6) -> 6
(set! d 8) -> 8
(*(- (+ 4 c) b) (div d a)) -> 12
; Rule Example
(if (= a b) c d) -> 8
;Predicate:
(> c d) -> nil
```


A Lisp GP system

A Lisp GP system is a large set of functions which are interpreted by evaluating the entry function

- Some are definitions of primitives you write!
  - » (defun protectedDivide …)
- Rest is software logic for evolutionary algorithms

Any GP system has a set of functions that are pre-defined (by compilation or interpretation) for use as primitives

also has software logic that handles

- Population initialization, iteration, selection, breeding, replacement

GP expressions are first class objects in LISP so the GP software logic can manipulate them as data as well as have the interpreter read and evaluate them

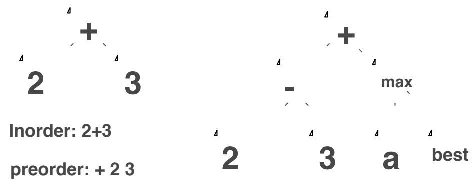
Details When Using Executable Expressions

- Sufficiency
  - Make sure a solution can be plausibly expressed when choosing your primitive set
    - » Functions must be wisely chosen but not too complex
    - » General primitives: arithmetic, boolean, condition, iteration, assignment
    - » Problem specific primitives
  - Can you handcode a naïve solution?
  - Balance flexibility with search space size
- Closure
  - Design functions with wrappers that accept any type of argument
  - Often types will semantically clash…need to have a way of dealing with this

Expression Representation

- Printing, executing: nested list of symbols
  - 3+2
  - (+ 2 3) ; same as above, different syntax
  - (3 2 +) ; same too
- Crossover/Mutation:
  - GP needs to be able to crossover and mutate executable expressions, how?
  - Expressions can be represented universally by an abstract syntax via a tree

Abstract Syntax Trees



Inorder: 2+3

preorder: + 2 3

Post-order: 2 3 +

Inorder: (2-3) + (a max best)

preorder: (+ (-2 3) (max a best))

Post-order: (2 3 -) (a best max) +)

- Whether parsed preorder (node, left-child, right-child) or postorder (left-child, right-child, node) or inorder (left, node, right) the expression evaluates to the same result
- (tree)GP uses an expression tree as its genotype structure

Agenda Review

Context: Evolutionary Computation and Evolutionary Algorithms

1. GP is the genetic evolution of executable expressions
   - Lisp S-expressions
   - Functions and terminals
   - Closure and sufficiency
   - Alternate representation for xo and mutation
     - » abstract syntax trees

Agenda

Context: Evolutionary Computation and Evolutionary Algorithms

1. GP is the genetic evolution of executable expressions
2. Nuts and Bolts Descriptions of Algorithm Components

Population Initialization

- Fill population with random expressions
  - Create a function set Φ and a corresponding function-count set
  - Create an terminal set (arg-count = 0), T
  - draw from F with replacement and recursively enumerate its argument list by additional draws from Φ U T.
  - Recursion ends at draw of a terminal
  - requires closure and/or typing
- maximum tree height parameter
  - At max-height-1, draw from T only
- "ramped half-half" method ensures diversity
  - equal quantities of trees of each height
  - half of height's trees are full
    - » For full tree, only draw from terminals at max-height-1

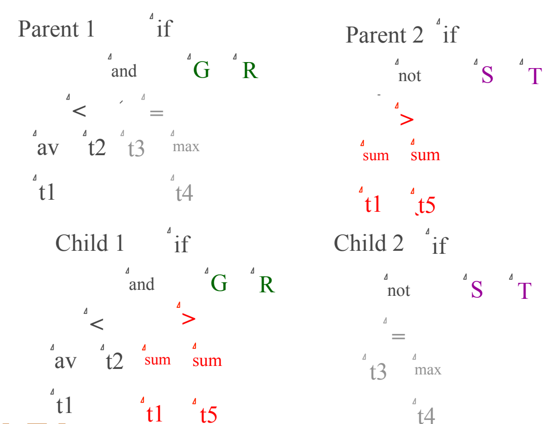
Determining a Expression's Fitness

- One test case:
  - Execute the expression with the problem decision variables (ie terminals) bound to some test value and with side effect values initialized
  - Designate the "result" of the expression
- Measure the error between the correct output values for the inputs and the result of the expression
  - Final output may be side effect variables, or return value of expression
  - Eg. Examine expression result and expected result for regression
  - Eg. the heuristic in a compilation, run the binary with different inputs and measure how fast they ran.
  - EG, Configure a circuit from the genome, test the circuit with an input signal and measure response vs desired response
- Usually have more than one test case but cannot enumerate them all
  - Use rational design to create incrementally more difficult test cases (eg block stacking)
  - Use balanced data for regression

Things to Ensure to Evolve Programs

- Programs of varying length and structure must compose the search space
- Closure
- Crossover of the genotype must preserve syntactic correctness so the program can be directly executed

GP Tree Crossover



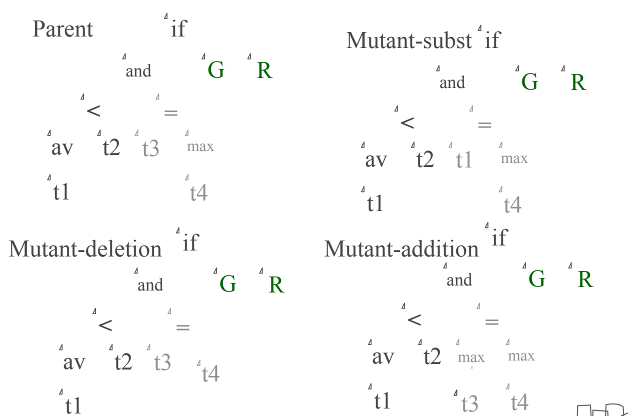
Tree Crossover Details

- Crossover point in each parent is picked at random
- Conventional practices
  - All nodes with equal probability
  - leaf nodes chosen with 0.1 probility and non-leaf with 0.9 probability
- Probability of crossover
  - Typically 0.9
- Maximum depth of child is a run parameter
  - Typically ~ 15
  - Can be size instead
- Two identical parents rarely produce offspring that are identical to them
- Tree-crossover produces great variations in offspring with respect to parents
- Crossover, in addition to preserving syntax, allows expressions to vary in length and structure (sub-expression nesting)

GP Tree Mutation

- Often only crossover is used
- But crossover behaves often like macro-mutation
- Mutation can be better tuned to control the size of the change
- A few different versions

HVL-Mutation: substitution, deletion, insertion



Other Sorts of Tree Mutation

- Koza:
  - Randomly remove a sub-tree and replace it
  - Permute: mix up order of args to operator
  - Edit: + 1 3 -> 4, and(t t) -> t
  - Encapsulate: name a sub-tree, make it one node and allow re-use by others (protection from crossover)
    - » Developed into advanced GP concept known as
      - Automatic module definition
      - Automatically defined functions (ADFs)
- Make your own
  - Could even be problem dependent (what does a subtree do? Change according to its behavior)

Selection in GP

- Proceeds in same manner as evolutionary algorithm
  - Same set of methods
  - Conventionally use tournament selection
  - Also see fitness proportional selection
  - Cartesian genetic programming:
    - One parent: generate 5 children by mutation
    - Keep best of parents and children and repeat
      - If parent fitness = child fitness, keep child

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Top Level GP Algorithm

```
Begin
    pop = random programs from a  set of operators and operands
    repeat
        execute each program in pop with each set of inputs
        evaluate each program's fitness
        repeat
            select 2 parents
            copy 2 offspring from parents
            crossover
            mutate
            add to new-pop
        until pop-size
    pop = new-pop
    until max-generation
        or
    adequate program found
End
```

Grow or Full

Ramped-half-half

Max-init-tree-height

•Tournament selection
•Fitness proportional selection
•Your favorite selection

Tournament size

Prepare input data
Designate solution
Define error between actual and expected

•HVL-mutate
•Subtree subst
•Permute
•Edit
•Your own

Mutation probs

Sub-tree crossover

Prob to crossover

Max-tree-height

Leaf:node bias

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Nuts and Bolts GP Design - Summary

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GP Preparatory Steps

Assume we have a GP system with internal expression evaluator.

1. Decide upon functions and terminals
   - Terminals bind to decision variables in problem
   - Combinatorial expression space defines the search space
2. Set up the fitness function
   - Translation of problem goal to GP goal
   - Minimization of error between desired and evolved expression when executed
   - Maximization of a problem based score
3. Decide upon run parameters
   - Population size is most important
     - Budget driven or resource driven
   - GP is robust to many other parameter choices
4. Determine a halt criteria and result to be returned
   - Maximum number of fitness evaluations
   - Time
   - Minimum acceptable error
   - Good enough solution (satisficing)

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Nuts and Bolts GP Design

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GP Parameters

- Population size
- Number of generations
- Max-height of trees on random initialization
  - Typically 6
- Probability of crossover
  - Higher than mutation
  - 0.9
  - Rest of offspring are copied
- Probability of mutation
  - Probabilities of addition, deletion and insertion
- Population initialization method
  - Ramped-half-half
  - All full
  - All non-full
- Selection method
  - Elitism?
- Termination criteria
- Fitness function
- what is used as "solution" of expression

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Nuts and Bolts GP Design

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Agenda Checkpoint

Nuts and Bolts GP Design

- How we create random GP expressions
- How we create a diverse population of expressions
- A general procedure for fitness function design
- How we mutate and crossover expressions
- Selection
- Put it together: one algorithm, at run level

Agenda

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ponyGP.js

- Javascript implementation
  - https://github.com/hembergerik/EC-Stable/tree/master/pony_gp/javascript
- Developed as part of ALFA's GP mooc curriculum initiative by Erik Hemberg, PhD.
- We will use Chrome's developer tool option to trace ponyGP
- We will use the webstorm IDE to examine the ponyGP.js data structures and code
- ponyGP.js performs simple symbolic regression

Agenda

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Reference Material

Where to identify conference and journal material

- Genetic Programming Bibiliography
  - http://www.cs.bham.ac.uk/~wbl/biblio/

Online Material

- ACM digital library: http://portal.acm.org/
  - GECCO conferences
  - GP conferences (pre GECCO),
- Evolutionary Computation Journal (MIT Press)
- IEEE digital library: http://www.computer.org/portal/web/csdl/home
  - Congress on Evolutionary Computation (CEC)
  - IEEE Transactions on Evolutionary Computation
- Springer digital library: http://www.springerlink.com/
  - European Conference on Genetic Programming: "EuroGP"

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GP Software

Commonly used in published research (and somewhat active):

- Heuristic lab (using grammar guided GP) , GEVA (UCD)
- EPOCHx
- DEAP, JGAP
- Java: ECJ, TinyGP,
- Matlab: GPLab, GPTips
- C/C++: MicroGP
- Python: Ponygp, oop_ponyGP.py, DEAP, PyEvolve
- .Net: Aforge.NET
- http://flexgp.github.io/gp-learners/index.html

Others

- http://www.epochx.org/index.php
  Strongly typed GP, Grammatical evolution, etc
  Lawrence Beadle and Colin G Johnson
- http://www.tc33.org/genetic-programming/genetic-programming-software-comparison/
  - Dated Feb 15, 2011

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Genetic Programming Benchmarks

Genetic programming needs better benchmarks

- James McDermott, David R. White, Sean Luke, Luca Manzoni, Mauro Castelli, Leonardo Vanneschi, Wojciech Ja´skowski, Krzysztof Krawiec, Robin Harper, Kenneth De Jong, and Una-May O'Reilly.
- In Proceedings of GECCO 2012, Philadelphia, 2012. ACM.

- Related benchmarks wiki
  - http://GPBenchmarks.org

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Software Packages for Symbolic Regression

No Source code available

- Datamodeler - mathematica, Evolved Analytics
- Eureqa II/ Formulize - a software tool for detecting equations and hidden mathematical relationships in data
  - http://creativemachines.cornell.edu/eureqa
  - Plugins to Matlab, mathematica, Python
  - Convenient format for data presentation
  - Standalone or grid resource usage
  - Windows, Linux or Mac
  - http://www.nutonian.com/ for cloud version
- Discipulus™ 5 Genetic Programming Predictive Modelling

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Reference Material - Books

- Genetic Programming, James McDermott and Una-May O'Reilly, In the Handbook of Computational Intelligence (forthcoming), Topic Editors: Dr. F. Neumann and Dr. K Witt, Editors in Chief Prof. Janusz Kacprzyk and Prof. Witold Pedrycz.
- Essentials of Metaheuristics, Sean Luke, 2010
- Genetic Programming: From Theory to Practice
  - 10 years of workshop proceedings, on SpringerLink, edited
- A Field Guide to Genetic Programming, Poli, Langdon, McPhee, 2008, Lulu and online digitally
- Advances in Genetic Programming
  - 3 years, each in different volume, edited
- John R. Koza
  - Genetic Programming: On the Programming of Computers by Means of Natural Selection, 1992 (MIT Press)
  - Genetic Programming II: Automatic Discovery of Reusable Programs, 1994 (MIT Press)
  - Genetic Programming III: Darwinian Invention and Problem Solving, 1999 with Forrest H Bennett III, David Andre, and Martin A. Keane, (Morgan Kaufmann)
  - Genetic Programming IV: Routine Human-Competitive Machine Intelligence, 2003 with Martin A. Keane, Matthew J. Streeter, William Mydlowec, Jessen Yu, and Guido Lanza
- Linear genetic programming, Markus Brameier, Wolfgang Banzhaf, Springer (2007)
- Genetic Programming: An Introduction, Banzhaf, Nordin, Keller, Francone, 1997 (Morgan Kaufmann)

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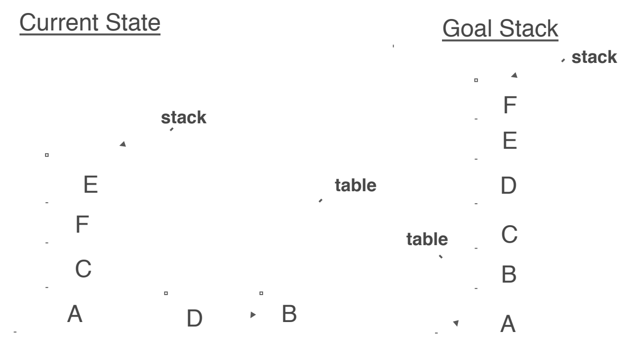
The Block Stacking Problem Koza-92



Goal: a plan to rearrange the current state of stack and table into the goal stack

Block Stacking Problem: Primitives

- State (updated via side-effects)
  - *currentStack*
  - *currentTable*
- The operands
  - Each block by label
- Operators returning a block based on current stack
  - top-block
  - next-needed
  - top-correct
- Block Move Operators return boolean
  - Return nil if they do nothing, t otherwise
  - Update *currentTable* and *currentStack*
  - to-stack(block)
  - to-table(block)
- Sequence Operator returns boolean
  - Do-until(action, test)
    - » Macro, iteration timeouts
    - » Returns t if test satisified, nil if timed out
- Boolean operators
  - NOT(a), EQ(a b)

Random Block Stacking Expressions

- eq(to-table(top-block) next-needed)
  - Moves top block to table and returns nil
- to-stack(top-block)
  - Does nothing
- eq(to-stack(next-needed)
  - eq (to-stack(next-needed) to-stack(next-needed)))
  - Moves next-needed block from table to stack 3 times
- do-until(to-stack(next-needed)
  (not(next-needed))
  - completes existing stack correctly (but existing stack could be wrong)

Block Stacking Fitness Cases

- different initial stack and table configurations (Koza - 166)
  - stack is correct but not complete
  - top of stack is incorrect and stack is incomplete
  - Stack is complete with incorrect blocks
- Each correct stack at end of expression evaluation scores 1 “hit”
- fitness is number of hits (out of 166)

Evolved Solutions to Block Stacking

eq(do-until(to-table(top-block) (not top-block))
do-until(to-stack(next-needed) (not next-needed)

- first do-until removes all blocks from stack until it is empty and top-block returns nil
- second do-until puts blocks on stacks correctly until stack is correct and next-needed returns nil
- eq is irrelevant boolean test but acts as connective
- wasteful in movements whenever stack is correct

- Add a fitness factor for number of block movements

do-until(eq (do-until (to-table(top-block)
(eq top-block top-correct))
(do-until (to-stack(next-needed) (not next-needed))
(not next-needed)

- Moves top block of stack to table until stack is correct
- Moves next needed block from table to stack
- Eq is again a connective, outer do-until is harmless, no-op

More Examples of Genetic Programming

- Evolve priority functions that allow a compiler to heuristically choose between alternatives in hyper-block allocation
- Evolve a model that predicts, based on past market values, whether a stock’s value will increase, decrease or stay the same
  - Measure-correlate-predict a wind resource
  - ICU clinical forecasting
    - » FlexGP
- Flavor design
  - Model each panelist
    - » Advanced methods for panelist clustering, bootstrapped flavor optimization
- Community Benchmarks
  - Artifical Ant
  - Boolean Multiplexor
- FlexGP
  - Cloud scale, flexibly factored and scaled GP

Agenda

Context: Evolutionary Computation and Evolutionary Algorithms

1. GP is the genetic evolution of executable expressions
2. Nuts and Bolts Descriptions of Algorithm Components
3. Resources and reference material
4. Examples
5. Deeper discussion (time permitting)

How Does it Manage to Work

- Exploitation and exploration
  - Selection
  - Crossover
- Selection
  - In the valley of the blind, the one-eyed man is king
- Crossover: combining
- Koza's description
  - Identification of sub-trees as sub-solutions
  - Crossover unites sub-solutions
- For simpler problems it does work
- Current theory and empirical research have revealed more complicated dynamics

Why are we still here? Issues and Challenges

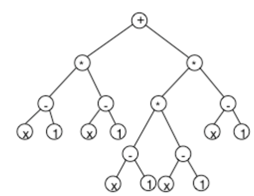
- Trees use up a lot of memory
- Trees take a long time to execute
  - Change the language for expressions
    - » C, Java
  - Pre-compile the expressions, PDGP (Poli)
  - Store one big tree and mark each pop member as part of it
    - » Compute subtrees for different inputs, store and reuse
- Bloat: Solutions are full of sub-expressions that may never execute or that execute and make no difference
- Operator and operand sets are so large, population is so big, takes too long to run
- Runs "converge" to a non-changing best fitness
  - No progress in solution improvement before a good enough solution is found

Runs "converge": Evolvability

- Is an expression tree ideal for evolvability?
- Trees do not align, not mixing likes with likes as we would do in genetic algorithm
- Biologically this is called "non-homologous"
- One-point crossover
  - By Poli & Langdon
  - Theoretically a bit more tractable
  - Not commonly used
  - Still not same kind of genetic material being swapped

Evolvability - modularity and reuse

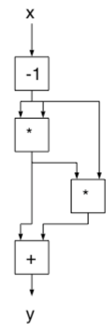
- Expression tree must be big to express reuse and modularity
- Is there a better way to design the genome to allow modularity to more easily evolve?



The representation of $(x-1)^2 + (x-1)^3$ in a tree–based genome

Evolvability: modularity and reuse

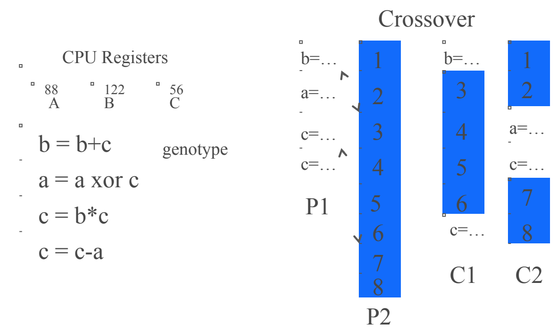
```
(1)   x=x-1
(2)   y=x*x
(3)   x=x*y
(4)   y=x+y
```



The dataflow graph of the $(x-1)^2 + (x-1)^3$ polynomial

Register Machine Genotype

- linear genotype, varying length, direct data

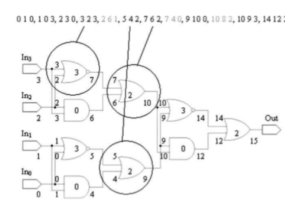


Register Machine Advantages

- Easier on memory and crossover handling
- Supports aligned "homologous" crossover
- Registers can act as poor-man's modules
- The primitive level of expressions allows for
  - Potentially more easily identifiable building blocks
  - Potentially less context dependent building blocks
- The register level instructions can be further represented as machine instructions (bits) and run native on the processor
  - AIM-GP (Auto Induction of Machine Code GP)
  - Intel or PPC or PIC, java byte code,
  - Experience with RISC or CISC architectures
  - Patent number: 5946673, DISCIPLUS system

Cartesian Genetic Programming

- Developer: Julian Miller
- operators and operands are nodes and data flow is described by genome
- Fixed length genome but variable length phenome
  - Integers in blocks
  - For each block, integers to name inputs and operator
- Unexpressed genetic material can be turned on later
- No bloat observed (plus nodes are upper bounded



Dealing with Bloat

- Why does it occur?
  - Crossover is destructive
  - Effective fitness is selected for
- Effective fitness
  - Not just my fitness but the fitness of my offspring
- Approaches
  - Avoid - change genome structure
  - Remove: Koza's edit operation
  - Pareto GP
  - Penalize: parsimony pressure
    - Fitness = A(perf) + (1-a)(complexity
- "Operator equalisation for bloat free genetic programming and a survey of bloat control methods", by Sara Silva and Stephen Dignum and Leonardo Vanneschi
  - GPEM Vol 13, #2, 2012

Examples:

- (not (not x))
- (+ x 0)
- (* x 1)
- (Move left move-right)
- If (2=1) action

No difference to fitness (defn by Banzhaf, Nordin and Keller)

Can be local or global

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Time Permitting

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The End

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