Genetic Programming 1: Introduction

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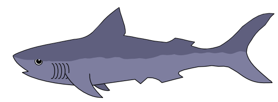
Introduction

- Learning
- Search Strategies
- Genetic Algorithms
- Genetic Programming



Types of Learning

- Supervised: Training examples with known inputs and outputs
- Unsupervised: No outputs are specified
- Reinforcement: Falls between the previous two types; A notion for the output quality is fed back to the learning algorithm

Search Strategies in Learning Systems

- Blind (uninformed) search, e.g., tree search
  - breadth-first-search strategy
  - depth-first-search strategy
- Hill climbing, e.g., simulated annealing
- Beam search: limited number of solutions at each vertex

Genetic Programming Overview

Representation	Tree structures
Recombination	Exchange of subtrees
Mutation	Random change in trees
Parent selection	Fitness proportional
Survivor selection	Generational replacement

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Genetic Algorithm: Basic Terms

POPULATION – a set of individuals which evolve according to rules of selection and genetic operators

FITNESS – a measure of 'goodness' assigned to each individual

SELECTION – a process of choosing high fitness individuals

GENETIC OPERATORS – used to perturb high fitness individuals

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Genetic Operators

- Mutation

Before 1 1 1 1 1 1 1

After 1 1 1 0 1 1 1

Mutated gene

Mutation usually happens with probability p_m for each gene

- Crossover

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Crossover Types

- Single-point crossover
- Double-point crossover
- Uniform crossover
- Weighted (arithmetic) crossover
- Analytical crossover

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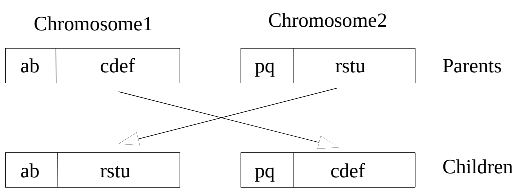
Single-Point Crossover



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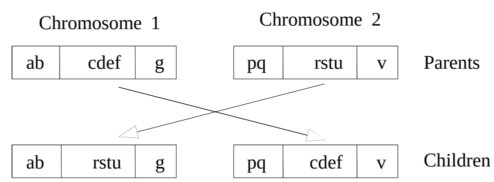
Double-Point Crossover



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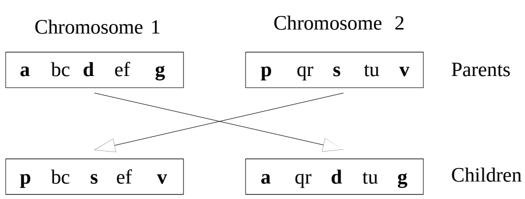
Uniform Crossover



The uniform crossover works on individual locus rather than segments of a chromosome. The probability of selecting a locus for exchange is called the mixing rate.
A mixing rate of 0.5 implies that each locus in the chromosome has an equal chance of being selected for replacement.

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Weighted (Arithmetic) Crossover (a)

- *Weighted (arithmetic) crossover* modifies rather than exchanges genetic material. It works at the chromosome level rather than individual loci. Weight *w* is selected before each crossover and then loci are randomly selected and exchanged.

- The expressions (1) and (2) represent the crossover process.

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Weighted (Arithmetic) Crossover (b)

$c_1 = wp_1 + (1 – w)p_2$ (1)

$c_2 = wp_2 + (1 – w)p_1$ (2)

where:

w = weight in [0, 1]

c_1 = child 1

c_2 = child 2

p_1 = parent 1

p_2 = parent 2

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Analytical Crossover

Analytical crossover works at a chromosome level. It considers the best and the worst fitness of the two selected parents (see (3) - (4))

$c_1 = p_b + s(p_b – p_w)$ (3)

$c_2 = p_b$ (4)

where:

s = scaling factor in [0, 1]

c_1 = child 1

c_2 = child 2

p_b = parent with the best fitness

p_w = parent with the worst fitness

Combining crossovers of different types is allowed

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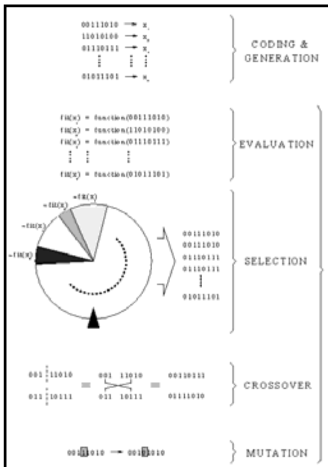

Genetic Algorithm: Process

Fitness function

- Coding
  - population size
- Evaluation
- Selection
- Crossover
  - probability of crossover
- Mutation
  - probability of mutation
- Number of generations

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Genetic Algorithm

Pseudo code

```
t = 0
Initialize P(t) to random individuals from the set {1,0}
WHILE termination condition is false
    Select individuals for re-production based on fitness
        Those not selected die
    Apply genetic operators to produce offspring
    Produce P(t+1) by adding offspring population to parent
    population
END
```

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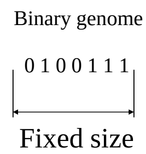
Genetic Algorithm

Drawbacks

- Some solutions are difficult to represent as binary strings.
- Computation time can be excessive.
- Computation not accurately reflect evolution.
- Relatively new concept.

Genetic Algorithm

Representation

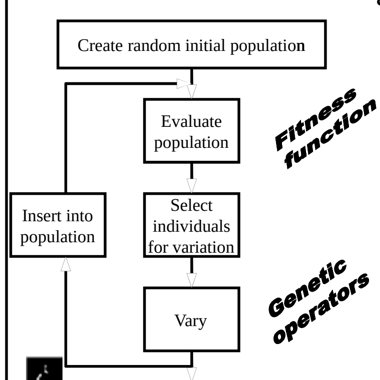


Genetic Programming

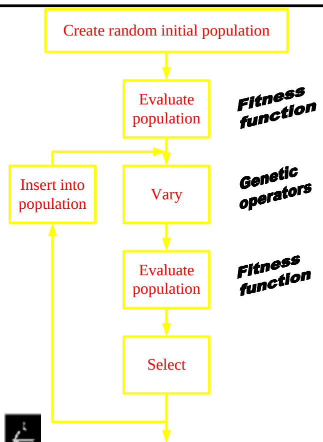
Representation:

No constraints on the representation

Genetic Algorithm: Steps



E.g., Crossover, mutation



Genetic Programming: Steps

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Genetic Programming: Population

Population: a set of individuals composed recursively from two sets:

- Set of N_{func} functions
  - arithmetic operations (+, -, *, …)
  - mathematical functions (sin, cos, exp, …)
  - Boolean operations (AND, OR, NOT)
  - subroutines or other domain-specific functions
- Set of N_{term} terminals
  - variable atoms (inputs, sensor information, state variables)
  - constant atoms (numbers)

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Comment: Analogy to Machine Learning

- A feature (input) in the training data set becomes part of the terminal set in GP

Thus, the features of the learning domain become the primitives used by GP to build a program structures

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Example

Genetic Programming: Population

The function set:

$$F = \{AND, OR, NOT\}$$

The terminal set:

$$T = \{d0, d1\}$$

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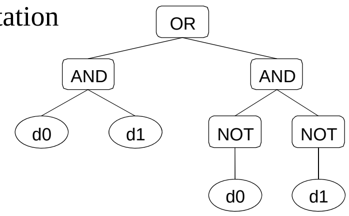
Example

Genetic Programming: Population

The even-2-parity function

- Graph representation



- S-expression; LISP representation

(OR (AND d0 d1) (AND (NOT d0) (NOT d1)))

Genetic Programming: Population

Graph example

Methods of generating initial population:

– **Full**: functions are chosen until the node reaches the maximum depth, therefore each branch of the tree has the same depth = max depth

– **Grow**: nodes are randomly selected from the function and terminal sets

– **Ramped half-and-half**

Generating Initial Population

Graph example

Ramped half-and-half method: enhances population diversity

Assume the maximum depth parameter = 6

- The population is divided equally among individuals to be initialized with trees having depths 2, 3, 4, 5, and 6
- For each depth group, half of the trees are initialized with full method and half with grow method

Genetic Programming: Fitness Function

- Fitness function is a metric
- Fitness function is problem specific
- Fitness function provides feedback to the algorithm which individuals should reproduce
- Fitness function measures how well a program has learned to predict outputs from inputs

Fitness Function

Example

$$f_p = \sum_{\text{All } i} |p_i - o_i|$$

p_i = (predicted) output from the GP program

o_i = (actual) output from the training set

Genetic Programming: Fitness

Types of fitness functions:

- raw fitness: not transformed
- standardized fitness: zero fitness value is always assigned to the fittest individual
- normalized fitness: all values are between 0 and 1

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Genetic Programming: Selection

Methods of selection:

- fitness-proportional selection
- truncation selection
- ranking selection
- tournament selection

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Fitness Proportional Selection

Probability of the individual i to be given a chance passing offspring to the next generation p_i

$$p_i = f_i / \sum_{\text{All } i} f_i$$

f_i = fitness of individual i

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Truncation Selection

Known also as (μ, λ) selection

- μ parents are allowed to breed λ offspring, out of which the fittest μ are used as parents for the next generation
- $(\mu + \lambda)$ selection is also used, where offspring and parents participate in the selection

Ranking Selection

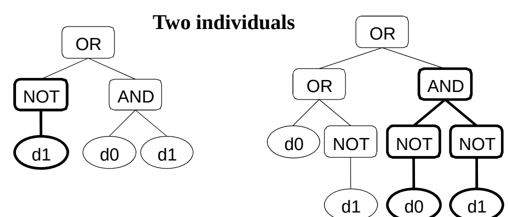
- Selection probability is assigned to an individual as a function of its rank
- Linear and exponential ranking functions are most often used

Tournament Selection

- Selection based on a competition within a subset of the population
- Tournament = a number of individuals is selected randomly

Genetic Programming: Genetic Operators

CROSSOVER



(OR (NOT d1) (AND d0 d1))

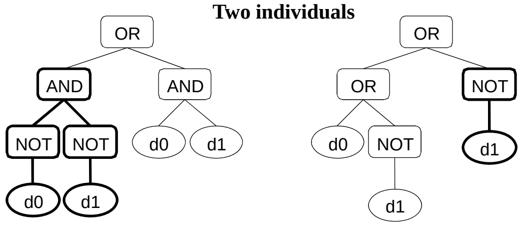
(OR (OR d1 (NOT d0)) (AND (NOT d0) (NOT d1)))

Slide 1

Genetic Programming: Genetic Operators

CROSSOVER

Two individuals



(OR (AND (NOT d0) (NOT d1)) (AND d0 d1))

(OR (OR d1 (NOT d0)) (NOT d1))

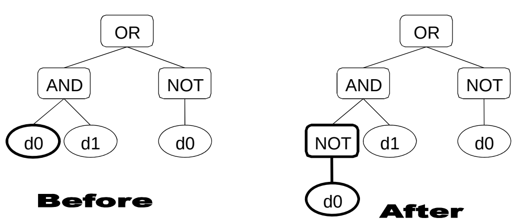
Comment: Generalized Crossovers

- “Intelligent” crossover: Selection of a crossover point that is less destructive to the offspring
- Crossover operator that learns
- Heuristic guided crossover
- Context sensitive crossover

Slide 2

Genetic Programming: Genetic Operators

MUTATION: within one individual



(OR (AND d0 d1) (NOT d0))

(OR (AND(NOT d0) d1) (NOT d0))

Genetic Programming: Parameters

- Major parameters
  - population size
  - number of generations
- Minor parameters
  - probability of crossover
  - selection of crossover points
  - size of S-expressions
  - probability of mutation
- Different ways of executing the runs
  - initial population
  - selection method
  - elitist strategy

Genetic Programming

- Representation of the problem
  - coding of individuals in the population
- Fitness function
  - evaluation of individuals in their capability to solve the problem

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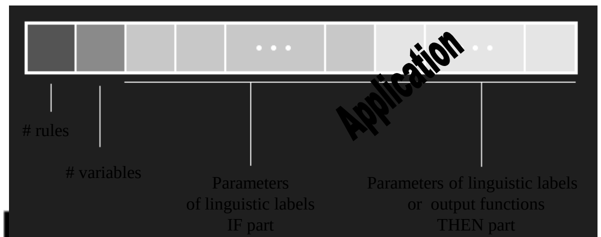
Genetic Programming: Fuzzy Rule-Based System Design

- Coding
  - each individual represents a single model, an array of floating-point numbers



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- Banzhaf, W., P. Nordin, R.E. Keller, and Frank D. Framcone (1998), *Genetic Programming*, Morgan Kaufmann, San Francisco, CA.
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